2020-10

Trust and Specialization: Evidence from U.S. States

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Juillet/ July 2020

Centre de recherche sur les risques
les enjeux économiques et les politiques publiques

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ABSTRACT

Is culture a determinant of a jurisdiction's comparative advantage? U.S. states that display a high level of generalized trust specialize in more "complex" industries that use contracts more intensively in their input-output relationships. This pattern is not driven by differences in states' other observable characteristics or by unobservable time-varying industry- or state-specific factors, and it does not reflect selection by export destination. Theoretical considerations suggest that trust may be endogenous to the location of complex industries. An instrumental variable strategy that leverages the contemporary trust impact of historical racial discrimination confirms that trust factors into the comparative advantage of U.S. states.

JEL Classification: F10, Z13.

Keywords: Trust, Complexity, Comparative Advantage, Specialization.

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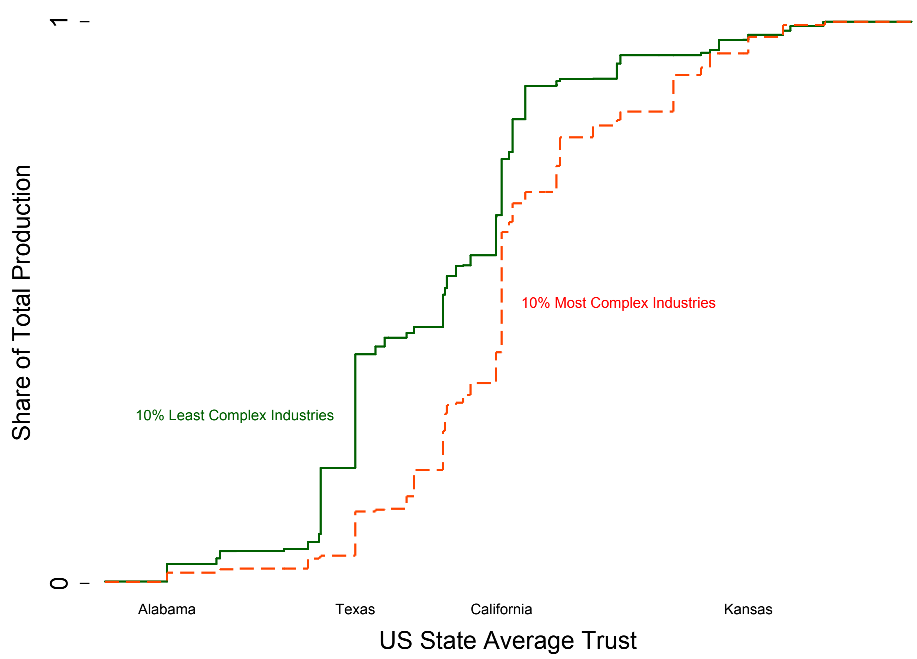
We thank Andrew Bernard, Matilde Bombardini, Carl Gaigné, Matthieu Crozet, Hartmut Egger, Keith Head, Miren Lafourcade, Claire Lelarge, Clément Nedoncelle, Sandra Poncet, Grégory Ponthière, Volker Nitsch, Andrew Rose, Farid Toubal, and seminar participants at British Columbia, Cologne (EEA), Darmstadt, INRA, Paris 1, Paris-Est Créteil, and Paris-Saclay for their helpful comments and insightful discussions. We are grateful to Thomas Michielsen for his help and his cooperation with the capital stocks data.

1 Introduction

Why do countries and regions specialize in different industries? In his presidential address to the International Economics Association, Samuelson (1969) argued that the theory of comparative advantage is perhaps the most successful testimony to the predictive power of the social sciences. Technology and endowments factor into the specialization of regions and countries.

Is culture another determinant of a region's economic specialization? In this paper, we establish that geographic differences in trust, which is one aspect of a society's culture, determine the location of industries among U.S. states. Using the standard definition of *generalized trust* as the trust people have towards a random person, we show that higher-trust states tend to attract (or to favor) more *complex* industries, i.e., industries that use contracts more intensively in their input-output relationships, because of shallow or non-existent spot markets for inputs.

Figure 1: Trust and the Cumulative Distribution of Production Across U.S. States



Notes: This figure reports the 2007 cumulative distribution of production across U.S. states ordered by their average trust levels. Trust by state is computed with data from the General Social Survey, and complexity is measured at the 4-digit level by using data on the contract intensity of an industry's input-output relationships. Output comes from the Annual Survey of Manufactures and the Economic Census.

Figure 1 illustrates that complex industries are located comparatively more in high-trust states. We plot the cumulative distribution function of the 2007 output of the 10% least complex and the 10% most complex industries by U.S. states ordered on the x-axis from the lowest to highest average trust. The distribution for the 10% least complex industries stochastically dominates the distribution for the 10% most complex, which means that high-trust states attract a comparatively larger share of complex industries. To construct this graph, we use the same data as in the rest of the paper. The average trust by state is computed with data from the General Social Survey (Algan and Cahuc, 2010), and complexity at the 4-digit level is measured by using Nunn (2007)'s U.S. data on the contract intensity of an industry's input-output relationships.[1]

The gist of our argument is that more complex industries mean higher verification costs, which trust may alleviate to some extent. We explore this argument in a simple formal model, where "complexity" captures the difficulty of verifying the quality of transactions between trade partners. In the absence of spot markets, or norms of quality and behavior, firms need to spend more resources on verification. Meanwhile, having more reliable trade partners lowers the economic benefit of monitoring, negotiating, and enforcing transactions. If the average trust at the state level captures equilibrium beliefs in the reliability of local trade partners, then it is arguably a substitute for verification. It may be that complex industries seek high-trust locations or survive better in high-trust locations: the result is that complex industries are located proportionately more in high-trust locations.

We estimate this prediction by using the geographic distribution of economic activity in the United States. Based on industrial output and exports disaggregated at the 4-digit level, we show that high-trust states specialize in more complex industries. To give an order of magnitude for our results, compare two states, Indiana (at the median of U.S. states in terms of trust) and Utah (one standard deviation higher in terms of trust), and take the example of motor vehicle parts, an industry with a complexity level one standard deviation above the median. If, ceteris paribus, Indiana's trust increases to the level of Utah, then our estimates predict that Indiana's production in motor vehicle parts would increase by 19%.

To establish our result, we address a number of possible identification threats. First, by focusing on the differences among U.S. states, we control for many confounding fac-

[1] Output comes from the Annual Survey of Manufactures and the Economic Census (See Appendix A for a more detailed discussion of the data.

tors that are common across all states, such as the trade policy, language, currency, institutions, and history.[2] Second, we control for time-varying industry- or state-specific characteristics with state-by-year and industry-by-year fixed effects (FE) with a difference-in-difference approach à la Rajan and Zingales (1998). Third, we address an endogeneity concern raised by our theoretical analysis with a plausible instrument of the geographical variation of trust among U.S. states, which was inspired by the work of Alesina and La Ferrara (2002) on the determinants of trust. To test the robustness of our results, we also decompose exports by destination to check that our results are not driven by certain states exporting to destinations with different characteristics. We consider a number of time-varying industry- and state-specific confounders, and we verify that the results apply both at the extensive and at the intensive margins of trade specialization.

Our results suggest that policies that aim to promote generalized trust would have large economic impacts. These policies would not have the same drawbacks as investing in human capital, which easily moves across borders. Contrary to most sources of comparative advantage, trust is local and hardly spills over to a region's neighbors (Baldwin, 2016). Moreover, our theoretical argument suggests a multiplier effect, where higher trust attracts more complex industries, whose presence, in turn, contributes to increasing trust further.

Our paper contributes to the literature that emphasizes the impact of trust on various aggregate economic outcomes, such as growth (Horváth, 2013; Algan and Cahuc, 2010; Dincer and Uslaner, 2010), financial development (Guiso et al., 2004), innovation (Kondo et al., Forthcoming; Nguyen, 2020), the performance of large organizations (La Porta et al., 1997), and the size of firms and their delegation of decisions (Bloom et al., 2012; Gur and Bjørnskov, 2017).[3] To this list of outcomes that trust impacts, we add economic specialization. To our knowledge, we are preceded in this direction only by Cingano and Pinotti (2016), who also study the role of trust in economic specialization, albeit with a very different mechanism and on more aggregated data. Using a 2-digit decomposition of industries, they show that high-trust Italian regions specialize in industries characterized by a greater need for delegation within firms. We build on this study in the following ways. First, based on a simple theoretical framework, we suggest another mechanism focused on

[2] Another advantage of this within-country approach is to increase the comparability of data.
[3] Although not directly related, a connected literature investigates the role of *bilateral* trust on bilateral trade (Guiso et al., 2009; Melitz and Toubal, 2019; Xing and Zhou, 2018).

solving the issue of verification *between* firms. Complex industries are not necessarily the same as industries that require intra-firm delegation; for instance, motor vehicle parts and steel product manufacturing share the same low level of delegation, but motor vehicle parts are seen as much more complex to produce than steel products. Second, with different data at hand, we can also provide further evidence of the mechanism in two ways. First, we uncover possible endogeneity in the relationship between trust and specialization, and we propose two instruments to establish that this relationship is plausibly causal. Second, we discuss the possibility of a composition issue in the export destination of different regions and verify that our results hold regardless of the country of destination.

The rest of the paper is organized as follows. Section 2 presents a simplified theory of how an industry's complexity and a jurisdiction's trust interact to explain specialization. Section 3 presents our identification strategy and the main results on the effect of trust on specialization. Section 4 discusses and examines the endogeneity concerns and the role of confounding factors. In Section 5, we explore the role of destinations with respect to composition issues and the extensive margin of specialization. Finally, in Section 6, we summarize and discuss our findings.

2 A Formal Discussion of Complexity, Trust, and Specialization

We propose a simplified theory of how an industry's complexity and a jurisdiction's trust may interact in a game-theoretic form. Since our goal is to take the theory to the data, it is useful to start by defining how the data relate to the variables that we introduce here.

Assumptions

Production in some industries embeds more complex input-output relationships than in others because of differences in contract intensity. We account for this by using a variable, labeled z, which measures the complexity of final downstream goods. Poultry processing or petroleum refineries, for instance, tend to have primary inputs that are bought and sold on organized or spot exchange markets. By contrast, the automobile and aircraft industries make intensive use of incomplete contracts and customized inputs that cannot be acquired on organized markets.

Firms within an industry characterized by complexity z can invest in their relationships with trade partners. They can spend resources supervising suppliers and verifying that transactions have been carried out. At a cost c, they can account for a large set of possible outcomes, identify reliable suppliers, and ascertain the quality of their inputs. For instance, c may represent a legal department, which ensures the reliability of the transactions with probability η. This probability increases when the legal department writes more complete contracts, but a more complex industry means a lower marginal efficiency of legal work. Finally, it is reasonable to assume that returns to legal sophistication decrease. Formally, we can write η as a function of c and z. Using subscripts to denote partial derivatives, our discussion translates into $\eta_1 > 0, \eta_2 < 0, \eta_{12} < 0,$ and $\eta_{11} < 0$.

In a very general formulation, a firm's profits π depend on the reliability of transactions η not only in the associated legal cost c but also in a more external factor called generalized trust θ. Trust is linked to the notion of "social capital," defined as "a set of beliefs, attitudes, norms, perceptions and the like that support participation" in a jurisdiction (Almond and Verba, 1963, as cited by Guiso et al., 2011).

Some reasonable assumptions allow us to simplify the discussion. More reliable transactions mean higher profits: $\pi_1 > 0$. Obviously, paying legal costs means less profits $\pi_2 < 0$: profits are quasi-linear in the costs, with $\pi_{12} = 0$, $\pi_{23} = 0$, and $\pi_{22} = 0$. Trust may have a direct effect on the profits of the firm, i.e., $\pi_3 > 0$, but for our purpose, it is most important to understand the effect that trust has on firm decisions. It can be plausibly argued that trust allows agents to depart from closed group interactions and to enlarge exchanges to anonymous others (Arrow, 1972; Algan and Cahuc, 2010). Therefore, if trust is an indication of the general degree of cooperation among agents within a society, then, for the firm, it is a substitute for verification: the benefit of verification decreases as trust increases, i.e., $\pi_{13} < 0$. However, there is reason to believe that the probability to detect a bad transaction, as measured by η, depends on trust.

Trust as a Source of Comparative Advantage

Now, if π_{11} is not too high, the firm's problem is adequately concave in c: the firm chooses c^* to maximize $\pi(\eta(c, z), c, \theta)$. Keeping the arguments implicit to simplify the notations, the envelope theorem yields that

$$\frac{d^2\pi(\eta(c^*, z), c^*, \theta)}{dz d\theta} = \eta_2 \pi_{13} > 0. \tag{1}$$

When all implicit parameters are kept the same, a higher complexity z means lower profits for the firm. However, trust dampens the effect of complexity. To limit the negative impact of complexity, we expect firms in more complex industries to locate in jurisdictions characterized by a higher level of trust. It is easy to see how, in a general equilibrium setting, this would translate into our main empirical hypothesis.

Prediction. *More complex industries will be located and thrive more in jurisdictions characterized by a higher level of generalized trust.*

We interpret this prediction to mean that trust enters into the sources of a jurisdiction's comparative advantage. We argue that this is a reasonable explanation for Figure 1.

The Endogeneity of Trust

Interestingly, our simple theoretical framework suggests that we should be concerned with the reverse mechanism: maybe complex industries more than less complex industries foster trust in the jurisdictions in which they have activities. To illustrate this, let us write the first-order condition for the firm's choice of c^*:

$$\pi_1(\eta(c^*, z), c^*, \theta)\eta_1(c^*, z) + \pi_2(\eta(c^*, z), c^*, \theta) = 0. \tag{2}$$

c^* depends on the industry's level of complexity z and on trust θ. The implicit function theorem yields

$$\begin{cases} c_1^*(z, \theta) = -\dfrac{\pi_{11}\eta_2\eta_1 + \pi_1\eta_{12}}{\pi_{11}\eta_1^2 + \pi_1\eta_{11}} \\ c_2^*(z, \theta) = -\dfrac{\pi_{13}\eta_1}{\pi_{11}\eta_1^2 + \pi_1\eta_{11}}. \end{cases} \tag{3}$$

Now, let us assume a profit function that is neither too convex nor too concave in its first argument, i.e., $-\eta_{12}/\eta_2 < \pi_{11}\eta_1/\pi_1 < -\eta_{11}/\eta_1$; that is, the firm is neither too risk-averse nor too risk-taking.[4] Under this assumption, let us notice that c_1^* and c_2^* are both negative. $c_2^* < 0$ means that trust allows firms to spend less on verification, which is hardly a surprising result.

More interestingly, $c_1^* < 0$ means that as complexity increases within an industry or between similar industries, firms spend less on verification. This may sound counter-

[4]In particular, our argument holds under most common specifications for a firm's profit that all assume risk neutrality.

intuitive, but complexity actually means that verification becomes less efficient. Firms reallocate resources away from verification towards what we can only assume are more productive uses. There is an argument that the resources not spent on verifying transactions characterize or reinforce trust, i.e., that θ is a decreasing function of c. This has the advantage of considering trust as endogenous. Because of this observation, we hope to capture that verification has an impact on trust. In our view, this argument may reflect two possible underlying mechanisms, and in both, we believe that there is a kernel of truth. First, verification may foster distrust, and conversely, less verification feeds into a higher level of trust. Second, when verification is too inefficient, the firm may be forced to be more trusting. Experimental results indeed suggest that contractual incompleteness leads to trusting behaviors (Bowles, 1998), as documented in 11th century Maghribi traders in (Greif, 1994).

This short theoretical discussion suggests a feedback effect between complexity and trust. Trust is relatively more attractive to high complexity industries than to low complexity industries. In turn, more complex industries have to rely more on trust than on formal verification, which fosters trust even further. It is important to note that we are not confident that the reverse causality mechanism that we have outlined actually matters empirically, and we are even less confident that it would be the most important mechanism. For our purpose, it is sufficient to establish that reverse causality is a threat that we need to address empirically.

3 Identification and Empirical Results

3.1 Identification

Following our formal discussion, we present here our empirical strategy to identify the effect of trust on specialization (see our Prediction) and to address the endogeneity of trust. We proceed in three steps. First, we focus on one country, the U.S., and exploit the differences in trust across states, which are otherwise identical in other relevant attributes. This within-country focus allows us to control for many confounding factors that are common across all states, such as the trade policy, language, currency, institutions, and history. Then, we follow Rajan and Zingales (1998)'s approach to make predictions about the within-state differences between industries based on the interaction between a state and an industry characteristic. We extend this approach to a panel setting where we can control for any time-variant state and industry-specific characteristics by using state-by-year and industry-by-year FE. Finally, we use an instrumental variable approach to further mitigate other potential sources of endogeneity in the relationship between specialization and trust, such as the reverse causality emphasized in the theory.

We implement our identification strategy by estimating the following equation:

$$X_{ist} \quad = \quad \beta_1(z_i \text{Trust}_s) + \beta_2(h_i H_{st}) + \beta_3(k_i K_{st}) + \alpha_{st} + \alpha_{it} + \epsilon_{ist}, \tag{4}$$

where X_{ist} represents a measure of specialization (production or exports) of a U.S state s in a 4-digit industry i at time t.[5] Our parameter of interest is β_1 and comes from the interaction between the complexity of industry i (z_i) and the average trust level of state s (Trust_s). The logic behind this interaction is simple: a positive coefficient β_1 indicates that states with a high level of trust produce or export relatively more in complex industries (i.e., high z_i industries). This implies that high-trust states specialize in complex industries as predicted by our theory (see our Prediction). The same logic applies to the factor endowment interactions, $h_i H_{st}$ and $k_i K_{st}$, where h_i and k_i are skill and capital intensities, while H_{st} and K_{st} are skill and capital endowments (Romalis, 2004).[6] If states that are abundant in a factor specialize in industries that intensively use this factor, then β_2 and β_3 will be positive. Equation (4) absorbs all time-varying state and industry characteristics by introducing state-by-year (α_{st}) and sector-by-year (α_{it}) FE.

We measure the production complexity z_i of a U.S. industry i with Nunn (2007)'s U.S. measure of the contract intensity of the input-output (I/O) relationships in industry i (see Appendix A.1 for details). Nunn's measure offers a relevant quantification of the complexity of production by determining which intermediate inputs are used, in what proportions, and of which type (differentiated, referenced, and homogeneous). Thus, when

[5] Production is the value added by a state from 2004 to 2012 at the 4-digit industry-level for manufacturing only. Exports are measured in values from each state to all countries in the world at the same 4-digit level from 2003 to 2012. We consider exports as an additional measure of specialization, first, because export data are more widely available and, second, to ensure that our results are not simply driven by composition issues, such that different states might specialize in different products because they sell to different countries. In Section 5.1, we consider a state's exports to a specific region or destination country. See Table 8 in the Appendix for more details on the construction of these variables and sources.

[6] States' skill endowment (H_{st}) is the log of the ratio of workers who complete college or higher to workers who complete at most high school. To measure states' stocks of physical capital (H_{st}), we follow Michielsen (2013) (see Appendix A.3). As in Nunn (2007), the data on the skill and capital intensities of production are from Bartlesman and Gray (1996), which reduces the sample to only manufacturing (i.e., 81 industries) (see Table 8 in the Appendix).

the proportion of differentiated inputs incorporated into production is higher, production relies less on organized and spot markets for inputs, and production relies more on complex I/O relationships. We measure the trust level of state s by relying on an attitudinal survey question from the General Social Survey (GSS) commonly known as Rosenberg's question, which is *"Generally speaking, would you say that most people can be trusted or that you need to be very careful in dealing with people?"* Respondents have only two possible answers: trust ("Most people can be trusted") or distrust ("Need to be very careful"). Our trust measure is the average proportion of people who trust in each state according to the GSS over the period of 1973-2006 (see Appendix A.2 for the details and descriptive statistics).

3.2 Estimation Results

Table 1 reports the estimates of Equation (4).[7] We first present the results with production as a measure of specialization (columns 1 to 3), and then, we present the results with exports (columns 4 to 7).

Trust and Output Specialization. In the first three columns of Table 1, the dependent variable, X_{ist}, represents the value added of state s in 4-digit industry i at time t. The regressions cover 79 industries and 49 U.S. states over the period of 2004-2012. The trust interaction estimates are positive and significant in the first three specifications, which supports our Prediction that trust is an important source of comparative advantage: high-trust states produce relatively more in more complex industries. The trust estimate in column 1 is slightly higher than the trust estimate in column 2 when factor endowments ($k_i K_{st}$ and $h_i H_{st}$) are added. The coefficients associated with the factor endowment interactions are also positive and significant, which indicates that a state abundant in one factor (capital or labor) specializes in industries that intensively use this factor.

The PPML estimator is used as a robustness check in column 3. This estimator provides a natural way to address zero values of the dependent variable and is consistent in the presence of heteroskedasticity (Santos Silva and Tenreyro, 2006). Zero-value observa-

[7] In the Appendix B.1, we also report the cross-sectional estimates of Equation (4) by averaging the dependent variables and the regressors over the years. The trust interaction estimates do not appear to be significantly different from those in Table 1.

Table 1: Trust and Specialization

Dependent Variable:	Value added$_{ist}$			Export Values$_{ist}$		
	in Logs		in Levels	in Logs		in Levels
Estimator:	OLS-FE		PPML-FE	OLS-FE		PPML-FE
	(1)	(2)	(3)	(4)	(5)	(6)
Trust Interaction: $z_i T_s$	**0.051**^{a}	**0.033**^{a}	**0.071**^{a}	**0.024**^{b}	**0.023**^{b}	**0.071**^{b}
	(0.010)	(0.010)	(0.019)	(0.010)	(0.010)	(0.025)
Capital Interaction: $k_i K_s$		0.478^a	0.716^a		0.309^a	0.622^a
		(0.843)	(1.345)		(0.081)	(0.181)
Skill Interaction: $h_i H_s$		4.918^a	3.700^a		1.346^a	1.311^b
		(0.238)	(0.208)		(0.343)	(0.661)
Observations	16,620	16,620	16,620	38,886	38,886	38,886
Adjusted R^2	0.536	0.547		0.738	0.740	
Fixed Effects:						
State$_s$	Yes	Yes	Yes	Yes	Yes	Yes
Industry$_i$	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Our regressions on value added (cols. 1 to 3) cover 79 industries and 49 U.S. states over the period of 2004-2012. The regressions on export values (cols. 4 to 6) cover 81 industries and 49 U.S. states over the period of 2003-2012. Robust standard errors are in parentheses, which are clustered by the state-industry, with ^{a}, and ^{b} denoting significance at the 1%, and 5% levels, respectively. Ordinary Least Squares with Fixed Effects (OLS-FE) are used in columns 1-2 and 4-5, while Poisson Pseudo-Maximum Likelihood with Fixed Effects (PPML-FE) is used in columns 3 and 6.

tions are not an issue for value added, however.[8] The role of heteroskedasticity could be more problematic, which may explain why the PPML estimates are somewhat quantitatively different from the OLS estimates without dismissing our interpretation of the role of trust on specialization.

Trust and Export Specialization. Because the data on state's exports provide a wider sectoral coverage per state and year than the data for value added, we pursue our analysis by using exports as our main measure of specialization in the last four columns of Table 1. The dependent variable, X_{ist}, now represents the world exports of state s in 4-digit industry i at time t. The regressions cover 81 industries and 49 U.S. states over the period of 2003-2012.[9] The OLS estimates of the trust interaction in columns 3 and 4 are positive, significant, and in the same order of magnitude as the production estimates. This result again confirms our Prediction that trust is important for comparative advantage:

[8] Some observations for value added are missing and are not recorded as zeros.

[9] Export data are available for the 50 states and the District of Columbia, but the trust survey measure is not available for Nebraska and Nevada.

high-trust states export relatively more in industries with more complex production.

To provide an order of magnitude of the trust effect, compare two states, Indiana (with a trust level $T_s = 39.3$ equal to the median value) and Utah (with a one standard deviation increase in trust $T_s = 50.5$) that export motor vehicle parts ($z_i = 0.685$, which represents one standard deviation above the median value). If Indiana's trust increases to Utah's level, then our estimation results predict that its exports in motor vehicle parts would increase by 19% [$= \exp(0.023 * 0.685 * (50.5 - 39.3)) - 1$].

The PPML estimator is again used as a robustness check in column 6. These estimates confirm the observed difference between the OLS (col. 5) and the PPML (col. 6) magnitudes[10] and the role of trust in the specialization of complex industries. Interestingly, the magnitudes of the PPML estimates of the trust effect on production (col. 3) and exports (col. 6) specialization are remarkably identical.

4 Endogeneity and Confounding Factors

4.1 The Endogeneity of Trust

Our theory emphasizes a reverse causality that runs from specialization to trust. States that are relatively more specialized in complex goods might also be prone to promote trust (see Section 2). We address the endogeneity in the relationship between trust and specialization with an instrumental variable approach inspired from the literature on trust determinants. Beyond individual determinants, such as age and education, trust appears to be negatively correlated with historical and contemporary experiences of racial discrimination and racial attitudes (Alesina and La Ferrara, 2002).[11] Therefore, states with higher racial discrimination tend to have a lower average level of trust.

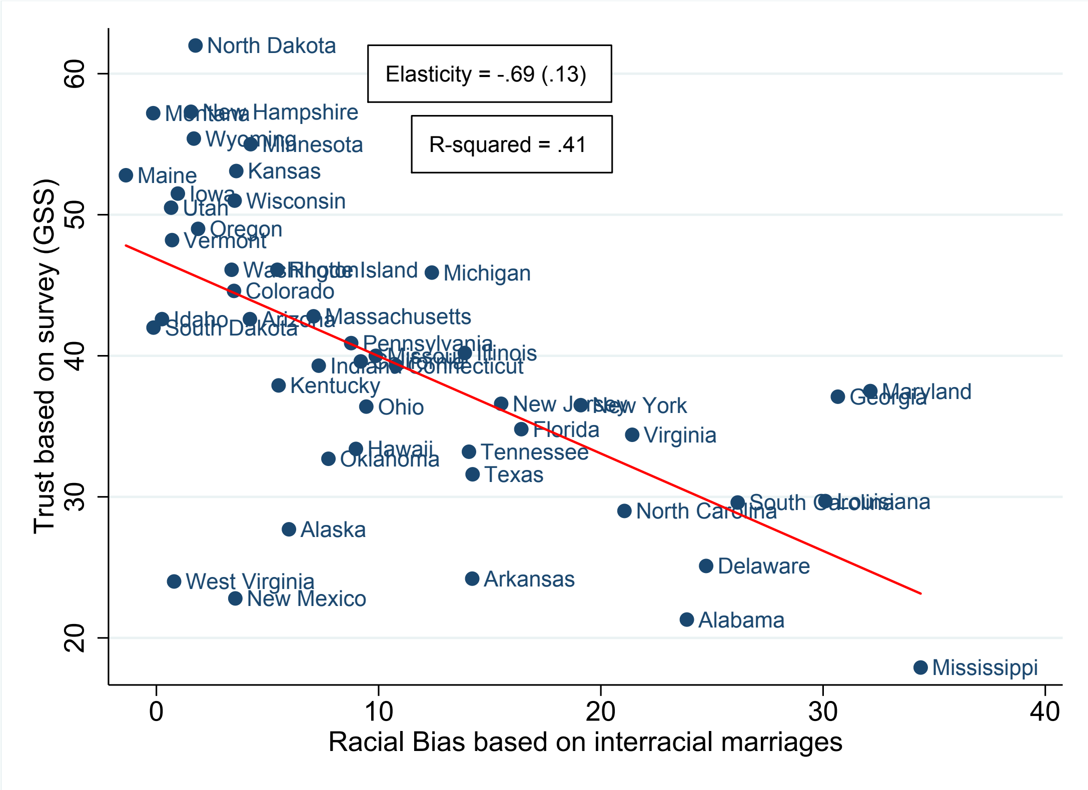
To capture the level of racial discrimination in a state, we use two variables. First, following Levine et al. (2008), we construct a state-specific racial bias index. This index equals the difference between the rate of interracial marriage that would exist if married people were randomly matched and the actual intermarriage rate.[12] Larger values of

[10]The sample in column 6 retains only positive export values. If we include null values, we obtain a sample of 39,528 observations and exactly the same PPL estimates.

[11]An important note is that we focus here on racial *attitudes* and not on the racial context. Although racial attitudes appear to have an undisputed effect on trust, there is still a debate on the impact (positive or negative) of the racial context (ethnic diversity) on trust.

[12]The random rate of interracial marriages is computed with available information in 2010 on the white

Figure 2: Survey-based Trust vs. Interracial Marriage Bias in the U.S.



Note: This figure plots a U.S. state's averaged generalized trust level, based on GSS surveys from 1973 to 2006, versus the intermarriage racial bias index in 2010 (see the Appendix for details). The regression line is depicted with a R^2 equal to 0.41. The elasticity coefficient from the OLS regression of trust on racial bias (-0.69) is reported with the standard error in parentheses (0.13).

the racial bias index indicate that intermarriage occurs less in practice than if marriage pairings were random. We interpret larger values as (partially) reflecting racial bias. We alternatively measure racial discrimination by using Stephens-Davidowitz (2014)'s proxy based on Google search queries in the United States. Stephens-Davidowitz constructs a proxy for a state's racial animus based on a non-survey source: the percent of Google search queries that include racially charged language.[13]

Both instruments are highly correlated with a state's average trust. Figure 2 plots the negative correlation between survey-based trust and intermarriage racial bias across states. We observe that ten of the 15 highest trust states also have the lowest intermarriage racial bias, and nine of the 15 lowest trust states also have the highest intermarriage racial bias. The pairwise correlation between intermarriage racial bias and trust equals -0.64, while the correlation between Google search racial bias and trust is -0.47.

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and black proportion of the married population in each state (see Table 8 in the Appendix).

[13] Stephens-Davidowitz (2014) collected data on the percentage of Google search queries that included the word *nigger(s)* between 2004 and 2007. The data are described in Table 8 in the Appendix.

Beyond relevance, the instruments must satisfy the exclusion restriction. We argue that there is no apparent reason for considering that racial discrimination might directly affect specialization within the manufacturing sector other than through trust. However, we are concerned that a common factor may explain both racial discrimination and economic specialization. In particular, although slavery was formally eradicated almost a century and a half ago, racial discrimination has its roots in slavery, and if its legacy persists currently, racial discrimination could explain specialization across U.S. states. Obviously, this would have been a major concern if we had focused on specialization between agriculture and manufacturing. We focus instead on specialization within states among manufacturing industries. The use of state FE allows us to control for the potential persistence of historical discrimination in particular states, while industry FE take into account the fact that one industry may be more affected than another by past discrimination. As a robustness check, we show that the addition of the share of slaves in the state's population in 1860 interacted with the complexity variable in Equation (4) is not statistically significant (see Section 4.2).

Table 2 displays the results of our instrumental variable estimation. The bottom row of this table shows the coefficients of the first-stage excluded instruments. As expected, our results indicate that states that have higher racial discrimination also have a lower level of trust. The large F-statistic and partial R-squared show that these instruments well explain the differences in trust across states.

The second-stage estimates are in line with the OLS estimates of Table 1. The capital and skill interaction variables are positive and significant. Our variable of interest, namely, the trust interaction variable, also has a positive and significant coefficient, which shows that states with a higher level of trust tend to export relatively more in complex industries. Therefore, even after accounting for an endogeneity bias in the relationship between trust and specialization, we still confirm that trust shapes the comparative advantage in complex industries.

4.2 Confounding Factors

Confounding factors may potentially bias the estimate of the trust interaction effect ($z_i T_s$) in Equation (4). Although the instrumental variable estimator also addresses the role of confounding factors, we believe that controlling more directly for them strengthens the

Table 2: Instrumental Variable Estimates

Second-Stage Estimates		
Dependent Variable:	Log Export Values$_{ist}$	
	(1)	(2)
Trust Interaction: $z_i T_s$	**0.047**^{a}	**0.094**^{a}
	(0.015)	(0.023)
Capital Interaction: $k_i K_{st}$	0.232^c	0.321^a
	(0.124)	(0.081)
Skill Interaction: $h_i H_{st}$	1.010^a	0.989^a
	(0.306)	(0.324)
Observations	38,204	38,886
R^2	0.744	0.744
State-by-Year Fixed Effects$_{st}$	Yes	Yes
Industry-by-Year Fixed Effects$_{it}$	Yes	Yes
Instruments:	Racial bias$_s \times z_i$	Racial animus$_s \times z_i$

First-Stage Estimates		
Dependent Variable:	Trust interaction ($z_i T_s$)	
Racial Bias$_s \times z_i$	-0.684^a	
	(0.021)	
Racial Animus$_s \times z_i$		-0.317^a
		(0.016)
F-test	1053.9	409.8
Partial R^2 of excluded instruments	0.408	0.191

Notes: Our regressions cover 81 industries and 49 U.S. states over the period of 2003-2012. Robust standard errors are in parentheses, clustered by state-industry, with ^{a} and ^{c} denoting significance at the 1%, and 10% levels, respectively. Estimates of the other variables in the first stage are not reported. "Racial bias" is computed based on the intermarriage racial bias index (col. 1) and "racial animus" is based on Google search queries (col. 2).

robustness of our results. In particular, we are concerned about the role of confounding factors at the industry-state level that is not controlled for in the estimated equation (beyond capital and skill interactions). One strategy to address the omitted variable bias is to introduce additional state-level control variables interacted with industry complexity (z_i), such as income per capita, skilled labor, economic freedom, judicial quality, and the share of slaves in 1860.

Table 3 reports the result when controlling for additional interaction terms. For comparison purposes, column 1 reports the benchmark estimation of Table 1 (column 5). The same benchmark estimation is reproduced in columns 4 and 7 because some confounding

Table 3: Robustness: The Role of Confounding Factors

	Dependent Variable: Log Export Values$_{ist}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Trust Interaction: $z_i T_s$	**0.023**^{b}	**0.023**^{b}	**0.021**^{b}	**0.029**^{a}	**0.029**^{a}	**0.029**^{a}	**0.056**^{a}	**0.061**^{a}
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.016)	(0.012)
Capital Intensity Interaction: $k_i K_{st}$	0.309^a	0.264^a	0.298^a	0.240^c	0.240^c	0.243^c	0.399^a	0.402^a
	(0.081)	(0.085)	(0.081)	(0.127)	(0.128)	(0.128)	(0.124)	(0.123)
Skill Intensity Interaction: $h_i H_{st}$	1.346^a	1.223^a	1.140^a	1.121^a	1.122^a	1.116^a	0.923^a	0.925^a
	(0.343)	(0.328)	(0.362)	(0.309)	(0.309)	(0.309)	(0.277)	(0.277)
Income per capita Interaction: $z_i I_{st}$		0.792^c						
		(0.429)						
Skilled labor Interaction: $z_i H_{st}$			0.292^c					
			0.163)					
Economic freedom Interaction: $z_i E_{st}$					-0.014			
					(0.139)			
Judicial quality Interaction: $z_i Q_s$						-0.228		
						(0.151)		
Share slaves (1860) Interaction: $z_i \phi_s$								0.377
								(0.760)
Observations	38,886	38,886	38,886	38,204	38,204	38,204	28,112	28,112
Adjusted R^2	0.738	0.738	0.738	0.735	0.735	0.735	0.726	0.726
Fixed Effects:								
State-by-Year$_{st}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-Year$_{it}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Our regressions cover 81 industries and 49 U.S. states over the period of 2003-2012. Robust standard errors are in parentheses and are clustered by state-industry, with ^{a}, ^{b} denoting significance at the 1%, 5% and 10% levels. OLS are used in all columns with multiple FE.

state variables are not available for the whole sample.[14]

In column 2, we add a new variable that interacts a state's income per capita I_{st} with industry complexity z_i. This additional variable controls for the potential specialization of wealthy states in more complex industries. This pattern seems to be plausible given the positive and slightly significant estimate (at the 10% level) of the new variable but without affecting the trust interaction estimate.

We further control for the possibility that states with a higher level of trust also have a higher level of skilled labor H_{st}, which is corroborated by the pairwise correlations (see Table 12 in Appendix B.2). These states are thus more likely to specialize in more complex industries. We account for this correlation by adding the interaction of the skill endowment variable H_{st} with z_i in column 3. As expected, the coefficient of the added interaction variable is positive but marginally significant.[15] Despite this addition, the

[14]See Table 8 in the Appendix A.4 for a description of the variables and how they are constructed.

[15]The lack of statistical significance of the added interaction ($z_i H_{st}$) can be explained by its high correlation with the skill interaction variable ($h_i H_{st}$). When dropping the skill interaction variable, the coefficient of the added interaction becomes significant at the 1% level without affecting the trust estimate.

trust interaction variable remains positive and highly significant.

The quality of institutions *per se* has been shown to be an important determinant of comparative advantage (Costinot, 2009; Levchenko, 2007; Nunn, 2007). We might therefore expect states with a higher level of trust to also have a higher quality of institutions, such as higher judicial quality or better contract enforcement, and thus be more likely to specialize in more complex industries. It is worth noting, however, that although states may have different rules or judicial interpretations of the federal laws, the room for large differences in the quality of institutions across states is limited. The U.S. Constitution requires local state courts to take into account judgments made by other state courts. Moreover, all states have adopted the Uniform Commercial Code, which harmonizes the law of sales and commercial transactions across the United States. However, time-varying differences across states may exist, and we attempt to proxy a state's institutional quality and interact it with the complexity variable z_i.

As a proxy for a state's institutional quality, we first use the economic freedom index computed by the Fraser Institute. This index is related to the rule of law as it encompasses the protection of contractual rights and private property. A low rule of law is assumed to reduce economic freedom. The economic freedom index is available annually at the state level, which is an important advantage compared to other proxies for institutional quality. We interact the economic freedom index E_{st} and industry complexity to create a new variable that we introduce in column 5 of Table 3. This additional interaction appears to be nonsignificant.[16] The trust interaction variable remains positive, statistically significant, and not different from the baseline trust interaction effect estimated on the same sample (see column 4).

Some characteristics of the judicial system differ across states (such as judicial terms, average salary in the judicial profession, or whether judges in state courts are elected or appointed), which could affect judicial quality. Therefore, we add a new interaction term in column 6 that controls more specifically for judicial quality Q_s by using an index constructed by Choi et al. (2009) (see Table 8 in the Appendix for details). The added interaction variable does not modify our main findings. The trust estimate is still positive and not different from the baseline trust interaction effect (see column 4).

[16]In unreported regressions, we also use the three sub-components of the overall index to construct three separate interactions (size of government, takings and discriminatory taxation and labor market freedom), and none of these variables affect our conclusions (the results are available upon request).

Finally, we control for the historical characteristics that may also bias the estimated impact of trust on specialization. At the time of the Civil War, the South was poorer than other U.S. regions. In particular, Southern states were much more dependent on agriculture and much less industrialized, which could be related to the plantation economy and slavery (see Acemoglu and Robinson, 2008). If this specialization pattern has persisted over time and if the slave-owning past had induced a lower level of trust today, then our trust estimate might be biased. To control for this concern, we add in column 8 a variable that interacts the ratio of the number of slaves in a state's population in 1860, ϕ_s, with the industry variable z_i. If a state's trust is indeed correlated with this state's 1860 share of slaves (see Table 12), the interaction estimate, $z_i\phi_s$, appears to not be significant and does not alter our main conclusion. The trust coefficient is very similar to the trust coefficient for the same sample (col. 7 versus col. 8).

Accordingly, the impact of trust on trade specialization holds across confounding factors. This suggests that our empirical strategy that exploits within-country variation in trust and introduces state-by-year FE allows us to mitigate most of the potential omitted variable problems.

5 The Role of Destinations

5.1 Composition Issues

The baseline results of Section 3 indicate that trust shapes comparative advantage. We now attempt to ensure that our results are not simply driven by composition issues, such as states exporting to different destinations with different characteristics. Exploiting the destination information of state's exports is useful to verify the following thought experiment: if trust helps establish and sustain complex input-output relationships to produce specific goods at home, specialization might not depend on the destination *per se* and the destination's trustworthiness.

Thus far, we reported the estimates of Equation (4) on an industry's total exports to the world. We now estimate Equation (4) for an industry's total exports to different regions in the world, namely, the European Union, Europe and Central Asia, the Middle East and North Africa, Sub-Saharan Africa, East Asia and the Pacific, South Asia, and

Table 4: Trust Effects across Regions

	Dependent Variable: Log Export Values$_{ist}$						
Exports to:	European Union	Europe & Central Asia	Middle East & North Africa	Sub-Saharan Africa	East Asia & Pacific	South Asia	Latin America & Caribbean
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Trust Interaction: z_iT_s	**0.055**^{a}	**0.059**^{a}	**0.048**^{a}	**0.047**^{a}	**0.024**^{b}	**0.054**^{a}	**0.037**^{a}
	(0.012)	(0.011)	(0.012)	(0.012)	(0.012)	(0.013)	(0.011)
Capital Interaction: k_iK_{st}	0.467^a	0.420^a	0.452^a	0.435^a	0.319^a	0.331^a	0.354^a
	(0.096)	(0.093)	(0.096)	(0.102)	(0.120)	(0.103)	(0.075)
Skill Interaction: h_iH_{st}	0.856^a	0.876^a	1.480^a	1.168^a	0.835^a	1.213^a	1.471^a
	(0.320)	(0.321)	(0.330)	(0.307)	(0.320)	(0.330)	(0.354)
Observations	35,458	35,869	31,074	26,741	36,127	25,598	36,186
R^2	0.70	0.711	0.643	0.581	0.675	0.572	0.728
Fixed Effects:							
State-by-Year$_{st}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-Year$_{it}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Our regressions cover 81 industries and 49 U.S. states over the period of 2003-2012. Robust standard errors are in parentheses and are clustered by state-industry, with ^{a} and ^{b} denoting significance at the 1%, and 5% levels, respectively. OLS are used in all columns with multiple FE.

Latin America and the Caribbean.[17]

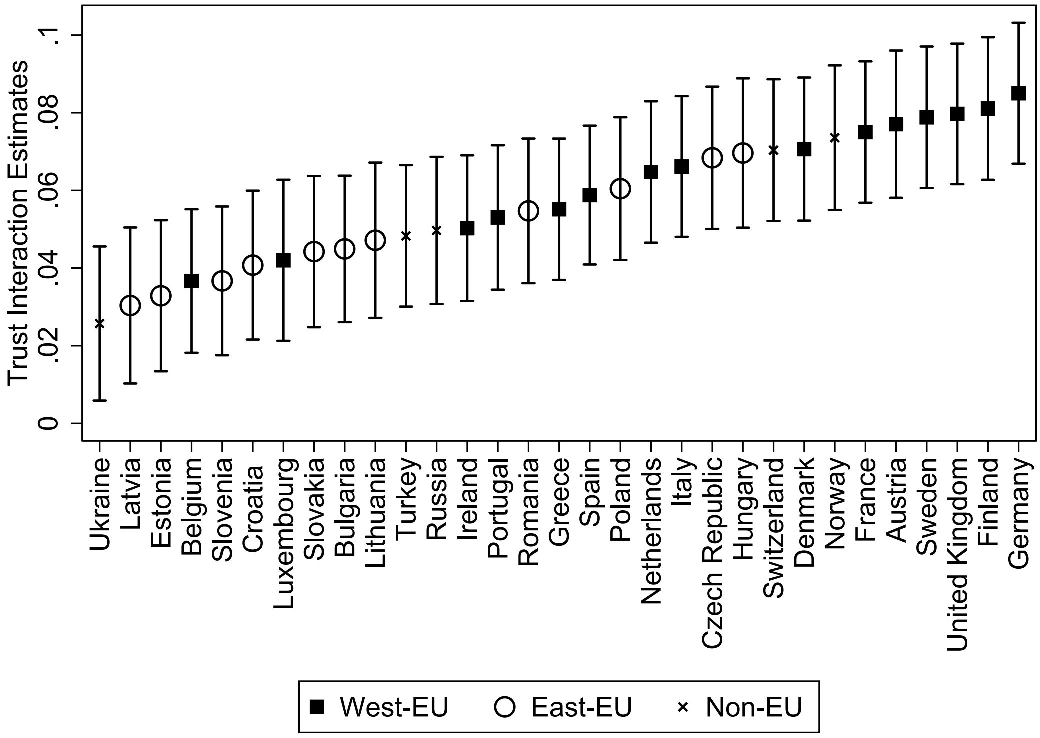
The results by destination region are displayed in Table 4. The estimates of the trust interaction are all positive and significant.[18] Even if we cannot test whether the differences across regions/specifications are statistically different from one another, we note that given the standard errors, the differences in magnitude across regions appear to be limited. We might have instead expected different trust effects depending on the trustworthiness of the destination. The European Union, for example, has on average a low level of corruption and a strong rule of law. However, the magnitude of the trust effect in the European Union (column 1) appears to be no different from that in Sub-Saharan Africa (column 4) and South Asia (column 6). Trust appears to affect the specialization of state exports regardless of the destination region.

One may be concerned that each region in Table 4 combines different types of countries. To address this issue, we now consider a state's exports to each individual destination country. We thus replace in Equation (4) the (z_iTrust_s) interaction with a triple interaction variable $(z_iTrust_sI_d)$, where I_d is an indicator variable for each destination country. This specification allows us to more accurately control for any omitted destination factor because we compare states with different levels of trust that export to the *same* destination market. Therefore, we estimate our model by including as many trust interactions

[17] Except for the European Union, we follow the World Bank classification of regions. See Table 10 in the Appendix for the list of countries and regions.

[18] In Table 4, we report only the OLS estimates. When we instead use an instrumental variable estimator, we obtain very similar results (the results are available upon request).

Figure 3: Trust Effects across European Countries



Note: This figure reports the OLS estimates and the 95% confidence interval of the trust interaction variable. We have replaced in Equation (4) the variable ($z_i Trust_s$) with a triple interaction variable ($z_i Trust_s I_d$), where I_d is an indicator variable for each destination country. We also condition the trust estimate on state-by-destination-by-year and industry-by-year FE.

as there are destination countries in the selected sample. We also condition the trust effect on a rich set of FE (state-by-destination-by-year and industry-by-year) to account for potential omitted variables. To ensure computation feasibility, we restrict our sample and attention to European countries.[19] We exploit the fact that despite being in the same continent, not all of the European countries have the same level of economic development, legal origin or quality of institutions. In particular, a distinction could be made between Eastern and Western European countries. These differences among countries may lead to different beliefs about their trustworthiness and reliability as importers.

The estimation results for the trust interaction coefficients are displayed in Figure 3 (the complete estimation results are available upon request). All trust interaction estimates are statistically significant, and the magnitudes are not related to any clear characteristics of the destination country. For instance, the trust effects in Hungary and

[19]We consider 26 current European Union members (Cyprus and Malta are not retained because they report positive imports in fewer than one-fourth of all sectors on average) and the five largest non-EU destinations—Norway, Switzerland, Turkey, Russia, and Ukraine.

Table 5: Extensive Margin and Specialization

Dependent Variable:	Log Number of Destinations$_{ist}$		Number of Destinations$_{ist}$
Estimator:	OLS-FE		PPML-FE
	(1)	(2)	(3)
Trust interaction: $z_i T_s$	**0.013**^{a}	**0.017**^{a}	**0.017**^{a}
	(0.003)	(0.003)	(0.003)
Capital interaction: $k_i K_{st}$		0.134^a	0.135^a
		(0.024)	(0.022)
Skill interaction: $h_i H_{st}$		0.104	0.073
		(0.121)	(0.057)
Observations	55,471	38,886	38,886
R^2	0.806	0.824	
Fixed Effects:			
State-by-Year$_{st}$	Yes	Yes	Yes
Industry-by-Year$_{it}$	Yes	Yes	Yes

Notes: Our regressions cover 81 industries and 49 U.S. states over the period of 2003-2012. Robust standard errors are in parentheses and are clustered by state-industry with ^{a} denoting significance at the 1% level. OLS and PPML are used in columns 1-2 and 3, respectively, with multiple FE.

Austria are fairly similar. Both countries are geographically close but have different levels of economic and institutional development.[20] Overall, the lack of significant differences across country estimates reinforces the evidence that trust shapes comparative advantages irrespective of the destination of exports.

5.2 Extensive Margin

The results presented to this point have shown the trust impact on the intensive margin of specialization, that is, the interaction effect of trust on the volume of production or the value of exports. We have also shown that the trust effect does not depend on the destination *per se*. However, trust may affect the extensive margin, that is, the number of destinations of trade. To study the extensive margin of specialization, we re-estimate our baseline specification (4), where the dependent variable X_{ist} is now the number of trading partners by industry-state-year.

The extensive margin results are depicted in Table 5. The OLS estimates, which are displayed in columns 1 and 2, suggest an additional effect of trust on specialization. Complex industries export to more destinations from high-trust states. We check the

[20] The average GDP per capita (in U.S.$ PPP) over the period of 2003-2012 is 2 times larger in Austria than in Hungary (World Development Indicators), and the average rule of law index is 2.3 times larger (Worldwide Governance Indicators).

robustness of this result with the PPML estimator (column 3) because the linear model neglects the nature of extensive margin data (characterized by the existence of lower and upper bounds), which may bias the estimates (see Santos Silva et al., 2014). However, the OLS and PPML estimates are virtually identical in columns 2 and 3, respectively.

6 Conclusion

In this paper, we show that trust, which is one aspect of a society's culture, determines a jurisdiction's comparative advantage. Our argument is that more complex industries mean higher verification costs, which trust may alleviate to some extent. We explore this argument in a simple formal model and estimate its main prediction: states with a high level of trust produce and export relatively more in more complex industries than states with low trust.

By showing that trust shapes comparative advantage, our paper contributes to the literature that finds that social norms and values affect economic performance. The results could be important for public policy because what countries produce and export matter (Hausmann et al., 2007). Moreover, because trust is localized in the region that implements the policy, this region obtains a large fraction of the benefit and spillovers (Baldwin, 2016, p. 229-230). Recommending a policy that might improve trust is a bit speculative, a rather unexplored area in the literature, and beyond the scope of this paper. Paul Romer suggests that promoting science also improves trust in a given society, although this is admittedly quite broad in scope and unspecific about details.[21]

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Appendix

A Data

A.1 A Measure of Production Complexity

We measure the production complexity z_i of a U.S. industry i with Nunn (2007)'s measure of contract intensity of input-output (I/O) relationships in U.S. industry i.[22] The following two key sources of data are used to construct z_i: (1) the U.S. input-output tables that allow determining which intermediate inputs are used in the production of final goods[23] and (2) the Rauch (1999) classification, which identifies differentiated versus non-differentiated inputs. Nunn's measure offers a relevant quantification of the complexity of production in an industry by determining which intermediate inputs are used, in what proportions, and of which type (differentiated, referenced, and homogeneous). Thus, when the proportion of differentiated inputs incorporated into production is higher, production relies less on organized and spot markets for inputs, and production relies more on complex I/O relationships.

We display in Table 6 the least and most contract-intensive industries in our sample. It is worth noting that *all* states produce and export in all 4-digit industries from the least to the most contract-intensive industries. We observe some variation, however. The top quartile of

[22]The z_i measure is assumed to be a fixed characteristic of an industry i and has been computed by using data from 1997.

[23]Ciccone and Papaioannou (2016) argue that estimations that rely on U.S. industry characteristics, such as U.S. I/O tables, as a proxy for unobservable industry characteristics of other countries may lead to biased estimates, depending on how technological similarity with the U.S. covaries with other country characteristics. We avoid this concern by using U.S. industry data to measure the U.S.'s industry complexity.

contract intensity ($z_i > 0.66$) concentrates 44% of U.S. exports, but this share ranges from 5.5% in Louisiana to 76.3% in Vermont.

Table 6: Industry contract intensity of production

Industries with the least contract-intensive input-output relations (lowest z_i)		
3241	Petroleum and Coal Products Manufacturing	0.04
3313	Alumina and Aluminum Production and Processing	0.06
3131	Fiber, Yarn, and Thread Mills	0.18
3253	Pesticide, Fertilizer, and Other Agr. Chemical Manuf.	0.19
3112	Grain and Oilseed Milling	0.20
3252	Resin, Synthetic Rubber, and Artificial Synth. Manuf.	0.21
3314	Nonferrous Metal (except Aluminum) Production and Process.	0.21
3311	Iron and Steel Mills and Ferroalloy Manufacturing	0.22
3312	Steel Product Manufacturing from Purchased Steel	0.22
3111	Animal Food Manufacturing	0.23
Industries with the most contract-intensive input-output relations (largest z_i)		
3333	Commercial and Service Industry Machinery Manufacturing	0.75
3162	Footwear Manufacturing	0.76
3366	Ship and Boat Building	0.79
3344	Semiconductor and Other Electronic Component Manuf.	0.81
3345	Navigational, Measuring, Electromed. and Control Inst. Manuf.	0.82
3364	Aerospace Product and Parts Manufacturing	0.88
3342	Communications Equipment Manufacturing	0.89
3343	Audio and Video Equipment Manufacturing	0.90
3341	Computer and Peripheral Equipment Manufacturing	0.93
3361	Motor Vehicle Manufacturing	0.98

Data source: Nunn (2007). NAICS 4-digit industries classification.

A.2 A Measure of Trust

The social norms that govern the behavior of community members generate shared expectations. In this respect, trust is linked to the notion of "social capital", which is defined as "a set of beliefs, attitudes, norms, perceptions and the like, that support participation" in a region (Almond and Verba, 1963, as cited by Guiso et al., 2011). We measure trust by relying on an attitudinal survey question from the General Social Survey (GSS) commonly known as Rosenberg's question, which is *"Generally speaking, would you say that most people can be trusted or that you need to be very careful in dealing with people?"* Respondents have only two possible answers: trust ("Most people can be trusted") or distrust ("Need to be very careful"). Our trust measure is the average proportion of people who trust in each state from the GSS over the period of 1973-2006. Note that averaging the level of trust over time by state makes sense because trust levels are relatively stable over time (see Algan and Cahuc, 2014). Although the within-time variation is low, we observe cross-state variation as reported in Table 7. The trust level varies from 17.9%

Table 7: Average Trust Levels in U.S. States, GSS, 1973-2006

Alabama	21.3	Missouri	40.0
Alaska	27.7	Montana	57.2
Arizona	42.6	New Hampshire	57.3
Arkansas	24.2	New Jersey	36.6
California	39.6	New Mexico	22.8
Colorado	44.6	New York	36.5
Connecticut	39.3	North Carolina	29.0
Delaware	25.1	North Dakota	62.0
District of Columbia	27.9	Ohio	36.4
Florida	34.8	Oklahoma	32.7
Georgia	37.1	Oregon	49.0
Hawaii	33.4	Pennsylvania	40.9
Idaho	42.6	Rhodes Island	46.1
Illinois	40.2	South Carolina	29.6
Indiana	39.3	South Dakota	42.0
Iowa	51.5	Tennessee	33.2
Kansas	53.1	Texas	31.6
Kentucky	37.9	Utah	50.5
Louisiana	29.7	Vermont	48.2
Maine	52.8	Virginia	34.4
Maryland	37.5	Washington	46.1
Massachusetts	42.8	West Virginia	24.0
Michigan	45.9	Wisconsin	51.0
Minnesota	55.0	Wyoming	55.4
Mississippi	17.9		

Data source: General Social Survey (GSS).

in Mississippi to 62% in North Dakota.

The survey-based measure of trust offers subjective information that certainly demands cautious interpretation. It is thus worth asking the following questions: What is the survey question measuring? Is it measuring trust(fullness) or trustworthiness?

Survey-based questions have been used extensively to measure generalized trust, which is defined as the trust that people have toward a random person. Then, a natural interpretation of the survey measure is that trust in a region is related to trust in a random person within the same region. However, Guiso et al. (2011) argue that trust is not only about beliefs in other people's trustworthiness within (or outside) a region but also about individual's preferences. Trust, as a preference, is shared by a community, is persistent over time, and is often passed on to community members through intergenerational transmission, formal education, or socialization. According to Fehr (2009), it seems quite likely that when people answer the survey question on trust, they consult either their own past experiences and behaviors or introspect how they would behave in situations involving a social risk.

Recent work challenges the validity of the survey question as an accurate measure of a person's trust(fullness). Using a trust game experiment,[24] Glaeser et al. (2000) show that trust is not correlated with the sender's behavior but with the receiver's behavior. This would imply that the survey question is a measure of trustworthiness and not of trust. However, Fehr et al. (2003) and Bellemare and Kröger (2007) show the opposite: the sender's behavior is correlated with survey-based measures of trust and not trustworthiness (of the receiver). More recently, Johnson and Mislin (2012) use an extensive dataset that contains observations of trust and trustworthiness behavior from replications of the trust game collected across 35 countries from more than 23,000 subjects. They find strong support for the interpretation that the trust question measures trust (of the sender) and not trustworthiness (of the receiver). Therefore, even if the literature has not reached a clear consensus on this debate, a majority of studies find that a survey-based measure captures not only beliefs about other people's trustworthiness but also the specific preferences of individuals, which can be either trust or distrust.[25]

A.3 Capital Stock Data

Following Michielsen (2013), we generate state capital stocks (K) by using a perpetual inventory method

$$K_{st} = (1 - z)K_{s,t-1} + I_{st},$$

where K_{st} in state s and year t is the total capital expenditure (I_{st}) augmented by the one-year lagged capital stock $K_{s,t-1}$ depreciated at rate z. Total capital expenditure I comes from the Annual Survey of Manufactures (U.S. Census Bureau) available from 1987 to 2012.[26] Capital expenditure covers manufacturing only. The initial capital stock K_{t-1} is computed based on a steady state approach (Harberger, 1978). One can consider a "normal" year or an average over 3 years such as

$$K_{t-1} = \frac{I_t}{z + g},$$

[24] In the standard trust game experiment, two players, a sender and a receiver, are anonymously paired. The sender decides how much of an endowment to give to the receiver. This amount is typically multiplied by 3 by the experimenter. Then the receiver decides how much of this increased endowment to allocate to the sender. The sender's behavior is used as a measure of trust, whereas the receiver's behavior proxies for trustworthiness.

[25] In reviewing the cultural traits that have so far received the most attention in the empirical literature, including trust, Alesina and Giuliano (2015) refer to cultural traits "as both preferences and beliefs, without distinguishing between the two; this is the approach taken in most papers that used these measures".

[26] Note that we use the earliest available data on annual capital expenditure. The Economic Census provides data for 1972, 1977 and 1982.

where I_t is the average over the period of 1987-1989, z is set to 0.035, and g is the average U.S. GDP growth rate ($g = 0.0383$).[27]

A.4 Data sources

Table 8: Data Description and Sources

Time-variant variables	
X_{ist}	Manufacturing exports of U.S. state s to each destination (world, region, country) by year t and industry i (NAICS 4-digit). Source: U.S. Census Bureau. Time period: 2003-2012. Number of 4-digit industries: 81. Number of U.S. states: 49.
VA_{ist}	Value added of U.S. state s at the 4-digit industry-level. Sources: Economic Census and Annual Survey of Manufactures. Both sources provide data for manufacturing only (i.e., classified in sectors 31-33 from the NAICS). Time period: 2004-2012. Number of 4-digit industries: 79. Number of U.S. states: 49.
H_{st}	Skill endowment. Computed as the log of the ratio of workers who have completed college or a Bachelor's program to workers who did not complete high school or completed only high school. Source: U.S. Census Bureau (Current Population Survey).
K_{st}	Capital endowment. See Section A.3. Source: U.S. Census Bureau (Annual Survey of Manufactures).
GDP per capita$_{st}$	Gross domestic product (GDP) by state (millions of current dollars). Source: Bureau of Economic Analysis.
Economic freedom index$_{st}$	Index of institutional quality provided by the Fraser Institute. It includes the three main components of the size of government, takings and discriminatory taxation and labor market freedom. Each component of the index ranges from zero to ten, where zero corresponds to little economic freedom, and ten corresponds to the highest level of economic freedom. Data for the District of Columbia are not available.

[27]Source: Bureau of Economic Analysis.

Table 8: Data Description and Sources (continued)

Time-invariant variables	
h_i	Skill intensity of production is computed as the ratio of non-production workers' wages in total wages in the United States (1996). Source: Bartlesman and Gray (1996).
k_i	Capital intensity of production is computed as the total real capital stock in industry i divided by the value added in industry i in the United States (1996). Source: Bartlesman and Gray (1996).
z_i	Complexity of production index at the 4-digit industry-level (see section A.1). We use contract intensities computed by Nunn (2007) by using input-output tables and the Rauch (1999) classification (proportion of intermediate inputs - weighted by value - that are neither traded on an organized exchange nor reference priced).
Trust_s	Trust is measured by averaging individual responses ("Most people can be trusted") in the General Social Survey (GSS) over the period of 1973-2006 (see section A.2). Data for Nebraska and Nevada are not available.
Judicial quality_s	Composite index constructed by Choi et al. (2009) using data on the decisions of all the judges of the highest court of every state for the period of 1998-2000. This index aggregates the following three measures of judicial quality: productivity (measured by the total number of opinions that a judge publishes each year); opinion quality (the number of times that out-of-state courts cite the published decisions of a state high court); and independence (which reflects whether judges' decisions are unrelated to partisanship). This index has the advantage of being transparent and objective compared to other rankings or evaluations that are based on the subjective views of experts, business lawyers, etc. It is computed as the simple average of the standard deviations for each state from the sample mean of each component. Data for the District of Columbia are not available.
Share Slaves $(1860)_s$	Number of slaves in the total population of each state in 1860. These data come from Decennial Censuses of the United States and are provided by Nunn (2008). Data for Alaska, Arizona, Colorado, Hawaii, Idaho, Montana, the District of Columbia, New Mexico, North Dakota, Oklahoma, South Dakota, Utah and Wyoming are not available.
Interracial marriages_s	Index computed as the difference between the actual rate of interracial (white/black) marriages (2008-2010) and a random rate computed by using the white (W) and black (B) proportion of the married population in 2010 $(2*(W*B)/((W+B)*(W+B-1)))$. Sources: U.S. Census Bureau (American Community Survey) and Pew Research Center analysis "U.S. Newly 'Married out' Couples of 2008-2010, by Race for States and Regions."
Google racial search_s	Proportion of Google searches that included the word nigger(s) between 2004 and 2007. Source: Stephens-Davidowitz (2014).

A.5 List of Countries

Table 10: List of Destination Countries of U.S. State Exports

Region	List of countries
Europe and Central Asia	Albania - Andorra - Armenia - Austria† - Azerbaijan - Belarus - Belgium† - Bosnia and Herzegovina - Bulgaria† - Croatia† - Cyprus† - Czech Republic† - Denmark† - Estonia† - Faroe Islands - Finland† - France† - Georgia - Germany† - Gibraltar - Greece† - Greenland - Hungary† - Iceland - Ireland† - Italy† - Kazakhstan - Kosovo - Kyrgyzstan - Latvia† -Liechtenstein - Lithuania† - Luxembourg† - Malta† - Macedonia - Moldova - Monaco - Montenegro - Netherlands† - Norway - Poland† - Portugal† - Romania† - Russia - San Marino - Serbia - - Slovakia† Slovenia† - Spain† - Sweden† - Switzerland - Tajikistan - Turkey - Turkmenistan - Ukraine - United Kingdom† - Uzbekistan
Middle East and North Africa	Algeria - Bahrain - Djibouti - Egypt - Iran - Iraq - Israel - Jordan - Kuwait - Lebanon - Libya - Malta - Morocco - Oman - Qatar - Saudi Arabia - Syria - Tunisia - United Arab Emirates - West Bank Administered by Israel - Yemen
Sub-Saharan Africa	Angola - Benin - Botswana - Burkina Faso - Burundi - Cameroon - Cape Verde - Central African Republic - Chad - Congo (Brazzaville) - Congo (Kinshasa) - Cote d'Ivoire - Equatorial Guinea - Eritrea - Ethiopia - Gabon - Gambia - Ghana - Guinea - Guinea-Bissau - Kenya - Lesotho - Liberia - Madagascar - Malawi - Mali - Mauritania - Mauritius - Mozambique - Namibia - Niger - Nigeria - Rwanda - Sao Tome and Principe - Senegal - Seychelles - Sierra Leone - Somalia - South Africa - South Sudan - Sudan - Swaziland Tanzania - Togo - Uganda - Zambia - Zimbabwe
East Asia and Pacific	Australia - Brunei - Burma - Cambodia - China - Fiji - French Polynesia - Indonesia - Japan - Kiribati - Korea North - Korea South - Laos - Macau - Malaysia - Marshall Islands - Micronesia - Mongolia - Nauru - New Caledonia - New Zealand - Palau - Papua New Guinea - Philippines - Samoa - Singapore - Solomon Islands - Taiwan - Thailand - Timor-Leste - Tonga - Tuvalu - Vanuatu - Vietnam
South Asia	Afghanistan - Bangladesh - Bhutan - India - Maldives - Nepal - Pakistan - Sri Lanka
Latin America and the Caribbean	Antigua and Barbuda - Argentina - Aruba - Bahamas - Barbados - Belize - Bolivia - Brazil - British Virgin Islands - Cayman Islands - Chile - Colombia - Costa Rica - Cuba - Curacao - Dominica - Dominican Republic - Ecuador - El Salvador - Grenada - Guatemala - Haiti - Honduras - Jamaica - Mexico - Nicaragua - Panama - Paraguay - Peru - Sint Maarten - St Kitts and Nevis - St Lucia - St Vincent and the Grenadines - Suriname - Trinidad and Tobago - Turks and Caicos Islands - Uruguay - Venezuela

Note: World Bank classification of countries by region. † European Union countries are marked by a dagger.

B Robustness of the Empirical Results

B.1 Trust and Specialization - Cross-sectional Estimates

Table 11: Trust and Specialization - Cross-sectional Estimates

Dependent Variable:	Value added$_{is}$			Export Values$_{is}$		
	in Logs		in Levels	in Logs		in Levels
Estimator:	OLS-FE		PPML-FE	OLS-FE		PPML-FE
	(1)	(2)	(3)	(4)	(5)	(6)
Trust Interaction: $z_i T_s$	**0.036**^{a}	**0.031**^{a}	**0.074**^{a}	**0.023**^{b}	**0.023**^{b}	**0.073**^{a}
	(0.012)	(0.012)	(0.018)	(0.010)	(0.010)	(0.025)
Capital Interaction: $k_i K_s$		0.489^a	0.888^a		0.332^a	0.747^a
		(0.142)	(0.199)		(0.090)	(0.215)
Skill Interaction: $h_i H_s$		0.614^a	0.696^a		0.735^a	0.275
		(0.238)	(0.208)		(0.214)	(0.215)
Observations	2,599	2,599	2,599	3,900	3,900	3,900
Adjusted R^2	0.587	0.592		0.765	0.767	
Fixed Effects:						
State$_s$	Yes	Yes	Yes	Yes	Yes	Yes
Industry$_i$	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Our regressions cover 49 U.S. states and 79 industries in the first 3 columns and 81 industries in the last three columns. We average exports, capital stocks and skill endowments over the period of 2003-2012, and we average the value-added over the period of 2004-2012. Robust standard errors are in parentheses and are clustered by state-industry, with ^{a}, and ^{b} denoting significance at the 1%, and 5% levels, respectively. OLS are used in columns 1-2 and 4-5, while PPML are used in columns 3 and 6. All regressions use a rich set of FE.

B.2 Correlation on Confounding Factors

Table 12: Correlation Matrix between Trust and Confounding Factors

	T$_s$	$\ln(I_{st})$	H_{st}	E_{st}	Q_s	ϕ_s
Trust: T_s	1					
ln(Income per capita): $\ln(I_{st})$	0.01	1				
Skilled labor: H_{st}	0.22^a	0.36^a	1			
Economic freedom index: E_{st}	0.04^a	0.32^a	-0.03^a	1		
Judicial quality: Q_s	0.07^a	0.02^a	0.02^a	-0.12^a	1	
Share slaves (1860): ϕ_s	-0.66^a	-0.45^a	-0.19^a	0.17^a	0.03^a	1

Note: Pairwise correlation coefficients with ^{a} denoting significance at the 1% level.