ONLINE APPENDIX

Agricultural Diversity, Structural Change, and Long-run Development: Evidence from the U.S.

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Contents

Appendix A. Additional Results and Robustness Checks

A.1 Alternative Measures of Agricultural Diversity

This section considers a number of alternative measures of agricultural diversity. I show that the main results of the paper are robust to adjustments that address potential concerns about measurement error in the agricultural production data, and that they are also robust to considering measures with different functional forms than the standard Hirschman-Herfindahl index.

Measuring agricultural diversity with production data from the 1860 Census of Agriculture is subject to some concerns. First, there is likely mismeasurement in the value of animals produced for the market. The Census collected data on the "value of animals slaughtered." While no printed instructions were issued with reference to the 1860 Census schedule, the collected data presumably refers to the value of animals slaughtered *on the farm*. Thus, the value of livestock sold and slaughtered *off the farm* would be ignored, leading to underestimation. Another issue is that, according to Wright (1979), both demand and yields for cotton were unusually high in 1859. Finally, there is the broad issue that I use gross output rather than value added data.

I address these concerns by considering a number of adjustments and alternative measures. To address measurement error in the value of animals produced for the market, I take advantage of the fact that the 1870 Census collected data on the "value of animals slaughtered or sold for slaughter" rather than "value of animals slaughtered." Both the 1860 and the 1870 Census also collected data on the "value of livestock" on the farm. To construct an alternative measure of animals produced for the market in 1860, I take the 1860 "value of livestock" and multiply it by the ratio of 1870 aggregate "value of animals slaughtered or sold for slaughter" to 1870 "value of livestock" for my sample of counties. Thus, I get county-level estimates of the 1860 "value of animals slaughtered or sold for slaughter" based on the 1860 "value of livestock" on the farm and the ratio between these two variables in 1870 Census. This measure is on average about 25% higher than the "value of animals slaughtered" in 1860, while the correlation coefficient between the two is 0.6. The correlation between my baseline index of agricultural diversity in 1860 and the one obtained when replacing the 1860 "value of animals slaughtered" by the estimates with the "livestock adjustment" just explained is 0.91.

To address the possibly exceptional character of cotton production value in the 1860 Census, I create an alternative measure using 1870 data and considering price and output data for corn (the main agricultural product) as a reference. In particular, I take corn output in

1860 and multiply it by the ratio of cotton output to corn output in 1870, and by the average ratio of cotton prices to corn prices between 1876 and 1900 (cotton prices are not regularly available before 1876). Thus, I get a county-level proxy of the 1860 cotton production without using the 1860 data on cotton output or price.[3] This measure is on average about 5.5% lower than the actual 1860 cotton production value, and the correlation coefficient between the two is 0.93. The correlation between my baseline index of agricultural diversity in 1860 and the one obtained after performing the "cotton adjustment" just explained is also 0.93.

Finally, I consider agricultural variety (i.e., the number of products present at the county level) in 1860 and in 1870 as alternative measures.[4] In these measures, each product is either zero or one, which alleviates concerns about mismeasurement in the value of animals produced for the market, or about abnormal cotton demand or yields in 1859, insofar as these issues mostly affect the intensive margin. In any case, calculating agricultural variety with the "livestock adjustment" or the "cotton adjustment" does not qualitatively change the results.

Considering variety as the relevant measure of diversity provides a check on the implications of using gross output rather than value added data. There is no clear principle indicating whether measuring agricultural diversity with gross output rather or value added data is most appropriate. I use gross output rather than value added data simply because the latter are not available and estimating them would require a large number of questionable assumptions. If using value added data was appropriate, using gross output data would generate measurement error. However, this concern does not apply when agricultural variety is used as a measure of diversity, since the number of products with non-zero value added is generally the same as the number of products with non-zero gross output.

Panel A of Table A.1 provides estimates OLS and IV of the effects of 1860 agricultural diversity, captured with the alternative measures discussed above, on population density in 2000 (in logs), for my preferred specification (controlling for state fixed effects and geo-climatic features). To facilitate comparison, the first two columns reproduce the results using the baseline measure of Ag. Diversity in 1860. In line with the IV strategy from the main analysis, I construct an IV for Ag.Variety using the predicted product shares obtained from the FML model (and considering as present all products with predicted shares above 0.05%). I use the same IV for Ag.Variety in 1860 and 1870. In all cases, the results confirm positive

[3] I also considered measures of cotton output in 1860 in which I average cotton output in 1850 and 1870 and/or continue using the 1860 price or replace it with its average 1876-1900 price (instead of using the ratio to corn prices). All these variations produce qualitatively the same results.

[4] A complete set of prices for 1869/1870 is not available, so I cannot calculate Ag. Diversity in 1870, though I can estimate it with 1870 quantities and 1860 prices. Estimating the long-run effects of diversity using this measure produces qualitatively the same results.

and significant effects of early agricultural diversity on long-run outcomes.

Table A.1. Estimated Effects of Ag. Diversity Using Alternative Measures

	Dependent variable: Ln Population Density, 2000									
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A. *Alternative Measures I*										
Ag. Diversity_{1860}	2.370	4.477								
	(0.539)	(1.045)								
Ag. Diversity_{1860} (livestock adjustment)			2.765	5.712						
			(0.605)	(1.330)						
Ag. Diversity_{1860} (cotton adjustment)					2.192	4.181				
					(0.547)	(1.002)				
Ag. Variety_{1860}							0.0466	0.207		
							(0.0103)	(0.0628)		
Ag. Variety_{1870}									0.0510	0.244
									(0.0108)	(0.0805)
Observations	1,821	1,821	1,821	1,821	1,821	1,821	1,821	1,821	1,819	1,819
R^2	0.354	0.329	0.358	0.317	0.349	0.327	0.343	0.098	0.347	.
Panel B. *Alternative Measures II (Indexes of Specialization)*										
Krugman Specialization Index	-1.034	-2.848								
	(0.285)	(0.578)								
Gini Coefficient			-10.47	-21.74						
			(1.961)	(4.100)						
Index of Inequality in Production Structure					-1.674	-4.584				
					(0.639)	(1.017)				
Entropy Index							-4.740	-8.954		
							(1.078)	(2.091)		
Coefficient of Variation									-3.026	-5.355
									(0.617)	(1.227)
Observations	1,821	1,821	1,821	1,821	1,821	1,821	1,821	1,821	1,821	1,821
R^2	0.340	0.283	0.367	0.315	0.337	0.291	0.354	0.329	0.361	0.338
State FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Geo-climatic controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: The mean of log population density in 2000 is 4.37. Robust standard errors clustered on 60-square-mile grid squares are reported in parentheses.

I also check the robustness of the main results to adopting alternative measures of diversity. I consider several standard measures of specialization, for which higher values represent lower diversity: the Krugman Index of Specialization, defined as $\sum_i |\theta_{ic} - \theta_i|$, where θ_i is the share of product i in total agricultural output in the sample; the Gini coefficient of product shares; an index of Inequality in Production Structure proposed by Cuadrado-Roura et al. (1999), defined as $\sum_i (\theta_{ic} - \theta_i)^2$; an entropy index, defined as $E(\alpha)_c = \frac{1}{N\alpha(\alpha-1)} \sum_i \left[\left(\theta_{ic}/\bar{\theta}_{ic} \right)^2 - 1 \right]$, where $\bar{\theta}_{ic}$ is the average product share in county c (which is always equal to 1/36), and α, the weight given to distances between product shares at different parts of the distribution, is set equal to 2; and finally, the coefficient of variation of product shares, defined as $\sigma_{\theta_{ic}}/\bar{\theta}_{ic}$, where $\sigma_{\theta_{ic}}$ is the standard deviation of the shares in county c.

Panel B of Table A.1 provides OLS and IV estimates of the effects of 1860 agricultural diversity (actually, specialization), captured by these alternative measures, on population density in 2000 (in logs). The IV for each measure of specialization is constructed by replacing the actual product shares with the predicted shares from the FML model. In all cases, the results indicate significant negative effects of specialization, that is, positive effects of diversity.

A.2 Additional Controls for Distances to Waterways and the Fall Line

This appendix shows that the results are robust to controlling for distance to steamboat navigated rivers, distance to canals, and distance to the fall line in various flexible specifications. Market access and travel time to urban centers are likely to affect early diversification as well as the outcomes of interest, possibly in non-monotonic ways (Ashraf et al., 2010; Özak et al., 2018).

Table A.2 reports the coefficient estimates from OLS and IV regressions of 2000 population density (in logs) on 1860 agricultural diversity obtained when I add further (and more flexible) controls. First, in columns (1)-(2), I take the cubic polynomials in distance to steamboat navigated rivers, distance to canals, and distance to the fall line, and interact each term with dummies for each of the three Census regions in the sample, namely Northeast, Midwest, and South. The rationale is the effects of access to transportation networks and density are likely display regional heterogeneity.

In columns (3)-(4), as an alternative way to provide flexible controls, I create dummies for each of a few bins (0 to 10 miles, 10 to 30 miles, 30 to 60 miles, 60 to 100 miles, and above) for distance to rivers, distance to canals, and distance to the fall line. Finally, in the results reported in columns (5)-(6), I take the distance bin dummies and interact them with the region dummies.

Throughout all these robustness checks, the estimated effect of 1860 agricultural diversity on (the log of) 2000 population density is positive and significant.

Table A.2. Additional Controls for Distances to Waterways and the Fall Line

	Dependent variable: Ln Population Density, 2000					
	Specification 1		Specification 2		Specification 3	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Ag. Diversity$_{1860}$	2.149	2.441	2.207	4.432	2.280	4.255
	(0.368)	(0.863)	(0.545)	(1.057)	(0.408)	(0.985)
State FE	Y	Y	Y	Y	Y	Y
Baseline geo-climatic controls	Y	Y	Y	Y	Y	Y
Further controls for distances to rivers, canals, fall line:						
Cubic polynomials × Region FE	Y	Y	N	N	N	N
Distance bin dummies	N	N	Y	Y	N	N
Distance bin dummies × Region FE	N	N	N	N	Y	Y
R^2	0.477	0.476	0.374	0.346	0.433	0.412
Observations	1,821	1,821	1,821	1,821	1,821	1,821

Notes: The mean of log population density in 2000 is 4.37. Robust standard errors clustered on 60-square-mile grid squares are reported in parentheses.

A.3 Agricultural Specialization Patterns and Development

The effects of particular specialization patterns have attracted considerable attention from economic historians. Engerman and Sokoloff (1997, 2002) argue that climate and soil quality historically affected crop choice, which in turn led to divergent paths of development; in particular, they emphasize that specialization in cotton, sugar, rice, tobacco, and coffee favored slave plantations and thus generated inequalities that harmed long-run performance (see also Nunn, 2008; Bruhn and Gallego, 2012).

Other contributions highlight the effects of specialization in other crops through different mechanisms. Goldin and Sokoloff (1984) argue that the relative productivity of women and children in hay, wheat, and dairy was relatively low, and thus specialization in these products lowered the costs of hiring workers for industrial firms (see also Goldin and Sokoloff, 1982). Earle and Hoffman (1980) point out that wheat, corn, and livestock had highly seasonal labor requirements, which also lowered labor costs for the industrial sector. Sokoloff and Dollar (1997) also emphasize the high seasonality of grains, but they argue that the availability of cheap seasonal labor could hinder the adoption of more efficient manufacturing technologies. Vollrath (2011) proposes a model in which specialization in crops with high labor elasticity (e.g., rice) reduces the positive effects of agricultural productivity growth on industrialization.

This paper focuses on the effects of agricultural diversity beyond specific specialization patterns. As discussed in section III, the diversity index may be highly correlated with the shares of dominant crops. To avoid confounding the effects of agricultural diversity with those of specialization in specific crops, the estimating equation includes crop-specific dummy variables for the 5 major agricultural products (corn, cotton, animals slaughtered, hay, and wheat) and for plantation crops other than cotton (which take a value of 1 when the product, or group of products, has the largest share in a county's agricultural production). The dummy variables are meant to capture the notion of dominance reflected in terms such as "cotton counties" or "wheat counties."

This appendix shows that the results are robust to controlling for specific specialization patterns in different ways. In addition, to alleviate the concern that the results may be driven by a correlation between agricultural diversity and the extent of crop rotation, I include controls for clover, peas, and beans. Together with hay, these were the crops most commonly used in rotation schemes.

Table A.3 shows OLS and IV estimates of the effects of 1860 agricultural diversity on 2000 population density (in logs) with alternative sets of crop-specific controls.[5] To facilitate comparisons, columns (1)-(2) do not include any crop-specific controls and columns (3)-(4) include the dominance dummies as defined in the main analysis. Columns (5)-(6) include dominance dummies that take a value of 1 when the share for the corresponding crop (or group of crops) in the county's agricultural output is above 25%. Columns (7)-(8) include dominance dummies that take a value of 1 when the share is above the 75th percentile of the distribution of that share in the whole sample. Finally, columns (9)-(10) control for the actual shares.

The results confirm that agricultural diversity had a positive effect on long-run development. The coefficients on crop-specific controls suggest, in line with previous contributions, that early specialization in cotton and other plantation crops is negatively associated with long-run development. Specialization in animal production also appears to have a negative association with long-run development. For the purposes of this paper, the main takeaway from this analysis is that the estimated coefficients for agricultural diversity remain consistently positive and significant across specifications with different crop-specific controls.

[5] Only agricultural diversity is instrumented in these IV regressions; the results are qualitatively similar if the crop-specific controls are replaced by the corresponding values based on predicted shares from the FML model.

Table A.3. Effects of Agricultural Diversity Controlling for Specific Products

	Dependent variable: Ln Population Density, 2000									
	No crop-specific controls		Largest share dummies		> 25% dummies		> 75^{th} percentile dummies		Exact shares	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Ag. Diversity_{1860}	2.370	4.477	2.206	4.276	2.338	4.834	2.527	5.070	1.857	4.975
	(0.539)	(1.045)	(0.521)	(1.190)	(0.563)	(1.234)	(0.610)	(1.334)	(0.635)	(2.135)
Corn			-0.634	-0.734	-0.219	-0.277	-0.163	-0.0158	-2.484	-1.559
			(0.353)	(0.411)	(0.106)	(0.110)	(0.102)	(0.113)	(0.787)	(0.890)
Cotton			-0.991	-0.906	-0.532	-0.395	-0.391	-0.366	-2.522	-1.509
			(0.373)	(0.385)	(0.139)	(0.141)	(0.125)	(0.126)	(0.716)	(0.855)
Animals Slaughtered			-0.923	-1.082	-0.366	-0.456	-0.0613	-0.227	-2.553	-3.274
			(0.329)	(0.392)	(0.107)	(0.116)	(0.0824)	(0.103)	(0.811)	(1.227)
Hay			-0.193	0.298	-0.122	-0.0675	0.205	0.138	-1.027	-0.499
			(0.380)	(0.439)	(0.132)	(0.133)	(0.139)	(0.151)	(0.785)	(0.895)
Wheat			-0.331	-0.473	-0.0431	-0.0738	0.169	0.0805	-0.155	-0.389
			(0.349)	(0.417)	(0.104)	(0.104)	(0.0771)	(0.0902)	(0.654)	(0.766)
Tobacco+Cane+Rice			-0.965	-0.994	-0.487	-0.532	-0.330	-0.456	-2.689	-2.373
			(0.367)	(0.407)	(0.108)	(0.114)	(0.0780)	(0.106)	(0.653)	(0.696)
Clover+Peas+Beans							-0.171	-0.280	-10.00	-13.72
							(0.0779)	(0.0989)	(2.576)	(3,827)
State FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Geo-climatic controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Crop-specific controls	N	N	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1,821	1,821	1,821	1,821	1,821	1,821	1,821	1,821	1,821	1,821
R^2	0.354	0.329	0.372	0.349	0.367	0.334	0.375	0.346	0.401	0.364

Notes: The mean of log population density in 2000 is 4.37. The crop-specific controls are constructed in different ways across specifications, as indicated at the top of the columns. The combined share of Clover+Peas+Beans is never the largest share nor larger than 25%. Robust standard errors clustered on 60-square-mile grid squares are reported in parentheses.

A.4 Alternative Standard Errors

In the context of cross-sectional regressions in a sample of contiguous U.S. counties, the possibility of spurious correlations driven by spatial autocorrelation is an important concern. As visual inspection of Figure 1 suggests, agricultural diversity and each of the main outcomes of interest in my analysis display spatial autocorrelation. While the regressions throughout the paper use spatially clustered standard errors, this appendix offers further analysis to address concerns about spatial autocorrelation more thoroughly.

First, in Table A.4, I consider various standard errors that aim to account for spatial autocorrelation. I do this for the OLS and IV estimations of the three main specifications of the regression for Ln Population Density 2000.

Table A.4. Alternative Standard Errors

	Specification 1		Specification 2		Specification 3	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: Ln Population Density 2000						
Ag. Diversity_{1860}	2.020	3.641	2.370	4.477	2.137	4.463
Huber-White standard errors	(0.453)***	(0.775)***	(0.450)***	(0.839)***	(0.255)***	(1.031)***
Standard errors clustered by:						
60-square-mile grid-cells	(0.584)***	(0.973)***	(0.539)***	(1.045)***	(0.257)***	(1.142)***
State Economic Area	(0.553)***	(1.155)***	(0.505)***	(1.302)***	(0.268)***	(1.322)***
State	(0.533)***	(1.136)***	(0.473)***	(1.075)***	(0.267)***	(1.047)***
Conley (1999) standard errors with distance cutoff:						
25 miles	(0.572)***	(0.972)***	(0.521)***	(1.052)***	(0.252)***	(1.209)***
50 miles	(0.616)***	(1.212)***	(0.558)***	(1.316)***	(0.271)***	(1.364)***
100 miles	(0.626)***	(1.456)**	(0.563)***	(1.590)***	(0.275)***	(1.450)***
200 miles	(0.557)***	(1.563)**	(0.480)***	(1.706)***	(0.276)***	(1.243)***
300 miles	(0.536)***	(1.424)**	(0.372)***	(1.583)***	(0.218)***	(1.089)***
400 miles	(0.544)***	(0.975)***	(0.173)***	(1.352)***	(0.188)***	(0.635)***
Observations	1,821	1,821	1,821	1,821	1,821	1,821
State FE	Y	Y	Y	Y	Y	Y
Geo-climatic controls	Y	Y	Y	Y	Y	Y
Crop-specific controls	N	N	N	N	Y	Y
Socio-economic controls	N	N	N	N	Y	Y

Notes: The mean of log population density in 2000 is 4.37. Conley (1999) standard errors are computed using the `acreg` command created by Colella et al. (2019). *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

I consider the following alternative standard errors: Huber-White robust standard errors (a benchmark that does not address spatial autocorrelation in any way), errors clustered on 60-square-mile grid squares (as in the baseline estimations), clustered on State Economic Areas, clustered at the state level, and Conley standard errors with different distance cutoffs (25 miles, 50 miles, 100 miles, 200 miles, 300 miles, and 400 miles). In all cases, the results are robust.

Next, I conduct placebo exercises to assess whether the standard errors in my regressions provide effective ways to address concerns about spatial autocorrelation. Adopting an exercise proposed by Kelly (2019), I check whether spatial noise variables outperform (in terms of significance) agricultural diversity when they replace the latter in the OLS estimations of the same regression specifications considered in Table A.4. While Kelly (2019) only conducts this check for standard errors that do not account for spatial autocorrelation, I also do it for errors clustered by 60-square-mile grid-cells (the baseline in the paper), and Conley standard errors with multiple distance cutoffs. This allows me to assess whether these alternatives can effectively curtail spurious correlations.

To create the spatial noise variables, I generate 1,000 random variables covering all counties in the dataset (following a standard normal distribution), and then introduce spatial correlation by adding to each observation the values of the variable for all other observations weighted by the distance between counties (using a Gaussian decay function with a range of 210 miles).[6] I run 1,000 regressions for each specification, each time with one of the 1,000 spatial noise variables as regressor in place of agricultural diversity, and check whether spatial noise gets a smaller p-value than the one for agricultural diversity in the original regression. Finally, I report, for each specification, the fraction of the 1,000 regressions in which spatial noise outperforms agricultural diversity.

The results are displayed in Table A.5. For specifications 1 and 2, when using Huber-White robust standard errors (which make no corrections for spatial autocorrelation), we get sizable fractions of regressions (0.16 and 0.32, respectively) where simulated spatial noise has higher levels of significance than agricultural diversity. For specification 3, with the full set of controls, that fraction is only 0.01; this specification seems to be nearly immune to spurious correlations driven by spatial autocorrelation even in the absence of explicit corrections.

When standard errors are clustered by 60-square-mile grid-cells, the fractions where spatial noise outperforms agricultural diversity go down substantially for all specifications, sug-

[6] A distance of 210 miles is equivalent to approximately 3 degrees of latitude and roughly 4 degrees of longitude. For longitude this approximation corresponds to the line than runs through the middle of the US, at 40 degrees north; the distance between degrees of longitude is significantly smaller (larger) when moving north (south).

gesting that this clustering approach adequately addresses the issue. For Conley standard errors, even for relatively low distance cutoffs, I also see low fractions of regressions where spatial noise outperforms. In sum, it seems that the approaches to inference used in my analysis effectively curtail spurious correlations driven by spatial autocorrelation.

Table A.5. Statistical Significance of Spatial Noise versus Ag. Diversity

	Fraction of simulations where spatial noise outperforms Ag. Diversity		
	Spec. 1	Spec. 2	Spec. 3
Huber-White standard errors	0.16	0.32	0.01
Standard errors clustered by 60-square-mile grid-cells	0.09	0.19	0.00
Conley standard errors with distance cutoff 25 miles	0.11	0.20	0.00
Conley standard errors with distance cutoff 50 miles	0.05	0.10	0.00
Conley standard errors with distance cutoff 100 miles	0.02	0.07	0.00
State FE	Y	Y	Y
Geo-climatic controls	N	Y	Y
Crop-specific controls	N	N	Y
Socio-economic controls	N	N	Y

Notes: The dependent variable in the regressions is the log of population density in 2000, which has a mean of 4.37. All results are from OLS estimations. The table reports the fractions of regressions (out of 1,000) in which spatial noise regressors outperform (have a smaller p-value than) agricultural diversity. Conley (1999) standard errors are computed using the `acreg` command created by Colella et al. (2019).

A.5 Input-output Linkages

This section examines whether agro-processing and related industries with known input-output connections with specific agricultural products were more likely to be present the larger the importance of those agricultural products at the local level. To do this, I estimate linear probability models where the outcomes are indicator variables for the presence of specific industrial activities in county c in 1880 (the first year within the period under consideration with available full count Census data) and the key regressors are the shares corresponding to the relevant agricultural products in 1860.

I consider six industrial activities (and the agricultural products to which they are known to be linked): textile industries (linked to cotton, wool); tobacco manufactures (tobacco); bakery, confectionery, and related products (wheat, rye, cane sugar); beverage industries (rye, barley); meat products (animals); canning and preserving of fruits, vegetables, seafoods (orchards, market gardens).[7]

Table A.6 reports the coefficient estimates from OLS and IV regressions controlling for state fixed effects and geo-climatic features. The IV regressions use the predicted shares obtained from the FML model for each of the relevant agricultural products.

The results suggest that there were a number of input-output linkages through which the composition of agricultural production may have shaped industrial production patterns at the local level. In particular, it is consistent with the idea that agricultural diversity may have fostered manufacturing diversity by favoring entry into various agro-processing industries (which could in turn favor entry to other manufacturing activities).

A salient exception to the relevance of input-output connections among the ones considered here is the case of cotton and textiles, for which the IV estimate is negative (though not significant). Of course, it does not come as a surprise that the presence of cotton did not foster the development of textiles at the local level, as it is well-known that cotton production was concentrated in the South while textile industries were concentrated in the Northeast. In regard to the mechanisms analyzed in the paper, this does not mean that the presence of cotton production did not generate specific skills and knowledge that were potentially relevant for manufacturing at the local level.

[7]Textile industries comprise several industry groups in the 1950 Census classification system. I group them together because they have a common set of relevant agricultural inputs. I combine bakery products with confectionery and related products for the same reason. For beverage industries, corn was also a relevant input, but I exclude it because it was mostly used for other purposes (in particular, for feeding animals).

Table A.6. Input-output Linkages

	Dependent variable: Indicator variable for											
	Textile industries		Tobacco manufactures		Bakery, confectionery		Beverage industries		Meat products		Canning and preserving	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Cotton	0.102	-0.0549										
	(0.0888)	(0.144)										
Wool	0.335	0.964										
	(0.279)	(0.421)										
Tobacco			1.155	0.771								
			(0.168)	(0.290)								
Wheat					0.486	0.127						
					(0.129)	(0.491)						
Rye					1.513	4.450	0.362	6.007				
					(0.630)	(2.661)	(0.851)	(2.959)				
Cane Sugar					0.344	0.494						
					(0.167)	(0.187)						
Barley							6.452	8.729				
							(1.691)	(5.312)				
Animals Slaughtered									-0.0408	0.271		
									(0.109)	(0.266)		
Orchards											1.470	9.459
											(0.676)	(2.989)
Market gardens											0.915	0.106
											(0.278)	(0.493)
State FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Geo-climatic controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1,821	1,821	1,821	1,821	1,821	1,821	1,821	1,821	1,821	1,821	1,821	1,821
R^2	0.228	0.222	0.349	0.346	0.345	0.335	0.380	0.359	0.183	0.180	0.325	0.209

Notes: The outcomes are indicator variables for the presence of specific industrial activities in 1880 (as indicated for the columns) and the key regressors are the shares corresponding to the relevant agricultural products in 1860 (as indicated for the rows). Robust standard errors clustered on 60-square-mile grid squares are reported in parentheses.

Appendix B. A Model of Agricultural Diversity, Structural Change and Long-run Development

The multi-sector model of growth and structural change presented here offers one possible formal representation of the effects of agricultural diversity on development. A highlight of this representation is that entry into new sectors and the acquisition of new skills and ideas are interconnected dimensions of the process of structural change. The model predicts that diversity of skills positively affects industrial variety and overall industrialization, and has larger effects on sectors that require more skills. Moreover, initial differences in diversity lead to differences in long-run development.

I consider a small local economy, open to trade and labor flows. Free trade implies perfectly elastic demands for all goods. This allows me to abstract from the demand side and focus on the production side; consumption decisions play no role in the model. Meanwhile, under the simplest form of spatial equilibrium (with no amenities or congestion costs), free labor mobility implies that wages are equalized across locations. National wage levels—to which local wages are equalized—are taken as given.

These simplifying assumptions imply that productivity differentials across locations lead to differences in population density, without affecting wages. If labor was not perfectly mobile or if higher density generated congestion and increased living costs, then locations with higher productivity would have not only higher population density but also higher wages; the insights of the model about the effects of diversity on sectoral productivities, structural change and skills formation would be the same.

The key assumption underlying the persistent nature of the effects of diversity is that, in contrast to goods and labor, skills do not flow across locations. This stark assumption makes the model simpler and more transparent, but the implications are qualitatively the same if skills are assumed to be imperfectly immobile rather than completely immobile.

In the model, agricultural diversity is given by exogenous climatic conditions, and it determines the initial variety of skills. Industrial production comprises many sectors, each of which may be active or not, depending on expected profits. Skills required in each sector are complementary, and there are cross-sector spillovers within the local economy. Efficiency for each skill required in a sector depends on the set of established skills in other sectors.

In the presence of these complementarities and spillovers, higher diversity—which implies a wider range of skills—increases expected efficiency and profits, thus favoring entry into new sectors. In turn, expanding the range of active industrial sectors goes together with adoption of new technologies and formation of new skills. The essential source of growth is structural change, not only from agriculture to manufacturing, but most importantly within manufacturing—this is what drives the formation of new skills.

The model's emphasis on diversity of skills, and the mechanism whereby it fosters the acquisition of additional skills, echo Hausmann and Hidalgo (2011). The characterization of complementarities among skills resembles Kremer (1993), while that of cross-sector spillovers resembles Helsley and Strange (2002). Entry decisions are modelled similarly to innovation decisions in many endogenous growth models.

B.1 The Structure of Production

Production in the local economy comprises agricultural production and industrial production. Producers of all goods can sell as much as they want in the national market at a price equal to one (units of each good are defined to conform to this normalization), and can hire as much labor as they want at wage level $\bar{w}_t$, which is taken as given in the local economy. To keep notation simpler, the time subindex t and the local economy subindex c are dropped whenever it does not create confusion.

Agricultural Production

Agricultural production in a plot of land p is given by $Y_p = (A_p x_p)^{1-\sigma} L_p^{\sigma}$, where $\sigma \in (0,1)$, A_p is land productivity, x_p is land size, and L_p is labor hired in plot p. To maximize profits (given by $\Pi_p = Y_p - \bar{w} L_p$), the owner of plot p hires $L_p^* = \left(\frac{\sigma}{\bar{w}}\right)^{\frac{1}{1-\sigma}} A_p x_p$.

Total agricultural employment in the local economy is $L_a^* = \left(\frac{\sigma}{\bar{w}}\right)^{\frac{1}{1-\sigma}} \bar{A}_a X$, where $X = \sum_p x_p$ is total land, $\bar{A}_a = \sum_p \frac{x_p}{X} A_p$ is the average land productivity in the local economy. The distribution of land ownership does not affect total agricultural employment and production.

Agricultural output comprises a number of different crops. Agricultural diversity is determined by exogenous climatic features; for simplicity, it is taken as a primitive rather than explicitly modeled as the outcome of optimal crop choice.

Manufacturing Production

There are several industrial sectors (indexed by i), each of which may be active or not. Production in sector i is $Y_i = A_i^{1-\alpha} L_i^{\alpha}$, where A_i reflects sectoral productivity, L_i is labor employed in sector i, and $\alpha \in (0,1)$ reflects decreasing returns to labor (caused by limited entrepreneurial ability or some other fixed factor).

An active producer in sector i maximizes profits ($\Pi_i = Y_i - \bar{w} L_i$), which determines the optimal quantity of labor, $L_i^* = \left(\frac{\alpha}{\bar{w}}\right)^{\frac{1}{1-\alpha}} A_i$, as well as equilibrium output, $Y_i^* = \left(\frac{\alpha}{\bar{w}}\right)^{\frac{\alpha}{1-\alpha}} A_i$, and profits, $\Pi_i^* = (1-\alpha)\left(\frac{\alpha}{\bar{w}}\right)^{\frac{\alpha}{1-\alpha}} A_i$. Sectoral productivities are determined by local skills, as explained below.

Productivity and Local Skills

Productivity in sector i in local economy c at time t depends on the level of technology (T_t) and on the level of efficiency (E_{ict}):

$$A_{ict} = T_t \times E_{ict} \ .$$

The level of technology is the same across local economies (reflecting a common technology frontier) and across sectors (for simplicity), i.e., $T_{ict} = T_t$. Thus, productivity differences across locations and sectors are driven by differences in E_{ict}.

Efficiency levels in the different sectors of a local economy are determined by local skills. A key assumption is that skills are not mobile across locations.[8] The diversity of local skills is crucial because of the presence of skill complementarities and cross-sector spillovers, which are explained below.

Each sector i requires a set of specific skills indexed by $j_i = 1, ..., J_i$. Some sectors require only one or two skills, others require several: J_i captures the level of *complexity* of sector i. Sectoral skill requirements are the same in all local economies and time periods. A sector-specific skill j_i is performed with efficiency level $e_{j_ict} \in [0, \bar{e}]$, which may vary across local economies and over time.

The number of established skills at time t, denoted by $\Omega_{c,t}$, includes all the skills required by active industrial sectors in the local economy as well as the skills established in the agricultural sector. The number of skills established in agriculture, $\Omega_{A,c}$, is assumed to be time-invariant and strictly increasing in the initial level of agricultural diversity. The initial condition, corresponding to a period before the onset of industrialization, is $\Omega_{c,0} = \Omega_{A,c}$. I use $\Omega_{-i,c,t}$ to denote the number of skills in all sectors other than i ($\Omega_{A,c}$ is counted within $\Omega_{-i,c,t}$ for all i). In the rest of this section and in the next one, which focus on a single local economy, I drop the subindex c to simplify notation.

Skills within each sector are complementary. Featuring an "O-ring" property (Kremer, 1993), overall efficiency in sector i is given by

$$E_{it} = \prod_{j=1}^{J_i} e_{j_it} \ .$$

There are cross-sectoral spillovers within each local economy. Efficiency for a particular skill is given by the distance of that skill to a previously established skill in some other sector:

[8]This assumption is reasonable insofar as (i) skills cannot be codified and transmitted as disembodied knowledge, (ii) local skills are an attribute of locations rather than individual workers, i.e., hiring an individual worker from another location is not enough to establish the expertise available in that location, and (iii) hiring a large group of workers from another location is not possible because of coordination problems. The implications of the model are qualitatively the same if skills are assumed to be imperfectly immobile rather than completely immobile.

the local economy has high (low) levels of efficiency for doing things that are close (far) to what the economy was previously doing. More precisely, local efficiency for skill j required by sector i is given by $e_{j_i t} = \bar{e} - d_{j_i}$, where d_{j_i} is the distance between skill j_i and the closest previously established skill in a different sector.

Skills lie on a circle with radius $\bar{e}/\pi$ and their positions are independent draws from a uniform distribution on the circle. Thus, the pdf of d_{j_i} is $f(d) = \Omega_{\text{-}i,t\text{-}1}\bar{e}^{-\Omega_{\text{-}i,t\text{-}1}}(\bar{e}-d)^{\Omega_{\text{-}i,t\text{-}1}-1}$, and $\mathbb{E}\left[d(j_i)\right] = \frac{\bar{e}}{1+\Omega_{\text{-}i,t\text{-}1}}$. Distances between any two locations in the circle are between zero and $\bar{e}$, ensuring that $e_{j_i t} \in [0, \bar{e}]$.

Since the draws for the distances of different skills required by a sector and the closest ones in other sectors are independent, expected efficiency in sector i is given by

$$\mathbb{E}(E_{it}) = \mathbb{E}\left(\prod_{j}^{J_i} e_{j_i t}\right) = \left[\mathbb{E}(e_{j_i t})\right]^{J_i} = \bar{e}^{J_i}\left[1 - \frac{1}{1+\Omega_{\text{-}i,t\text{-}1}}\right]^{J_i} .$$

Active industrial sectors

There is one potential entrant in each industrial sector per period, who is assumed to be risk neutral. At the time of making the entry decision, the potential entrant only knows the expected level of efficiency. The minimum distances of required skills with respect to previously established ones become known only after paying the entry cost. Entrants produce for one period and then retire.

Entry is costly. Adopting frontier technologies requires micro-innovations and adaptation to the local economy. Thus, the number of active sectors in a given period is a measure of local technological dynamism—in this model, entry into new sectors is intrinsically linked with the acquisition of new ideas and the formation of skills. The entry cost, $F_t = \psi T_t^{1-\alpha}$, increases with the level of technology, reflecting that more advanced technologies are costlier to implement.

A sector becomes active if expected profits are larger than the entry cost. This defines a threshold in expected efficiency above which entry takes place:

$$\mathbb{E}(\Pi_{it}) \geq F_t \quad \Longleftrightarrow \quad \mathbb{E}(E_{it}) \geq \widetilde{E}_{it} = \frac{\psi}{(1-\alpha)\alpha^{\frac{\alpha}{1-\alpha}}}\left(\frac{\bar{w}_t}{T_t^{1-\alpha}}\right)^{\frac{\alpha}{1-\alpha}} .$$

Assuming that $g_{\bar{w}_t} = g_{T^{1-\alpha}}$, which ensures that wages and productivity grow at the same rate in the steady state, the threshold in expected efficiency is time-invariant, i.e., $\widetilde{E}_{it} = \widetilde{E}_i$.

The threshold for entry into sector i can be expressed as a threshold in the number of established skills in other sectors:

$$\widetilde{\Omega}_i = \frac{1}{\left(\frac{\bar{e}_i^J}{\widetilde{E}_i}\right)^{1/J_i} - 1} .$$

The number of active industrial sectors can then be expressed as $\sum_{i=1}^{I} \mathbb{1}_{\left[\Omega_{\text{-}i,t\text{-}1} \geq \widetilde{\Omega}_i\right]}$, where $\mathbb{1}_{\left[\Omega_{\text{-}i,t\text{-}1} \geq \widetilde{\Omega}_i\right]}$ is an indicator function that takes a value of 1 when $\Omega_{\text{-}i,t\text{-}1} \geq \widetilde{\Omega}_i$, i.e., when sector i is active, and 0 otherwise. Sectoral expected employment is given by $\mathbb{E}(L_{it}) = \mathbb{1}_{\left[\Omega_{\text{-}i,t\text{-}1} \geq \widetilde{\Omega}_i\right]} \times \mathbb{E}(L_{it}^*)$, where $\mathbb{E}(L_{it}^*) = \left(\frac{\alpha}{\bar{w}}\right)^{\frac{1}{1-\alpha}} \mathbb{E}(A_i)$ is expected optimal employment in an active sector.

B.2 Structural Change

This subsection explains how the diversity of a local economy affects the evolution of its production structure. I show that entry into any given industrial sector positively depends on the number of previously established skills in other sectors; so does the expected level of employment in the sector once activated, and more acutely so for complex sectors. Agricultural diversity, insofar as it increases the variety of local skills, positively affects entry and employment for all industrial activities. Thus, as I also show, agricultural diversity increases the total number of active industrial sectors and total expected employment in manufacturing.

In this framework, there is a close connection between diversity in production and diversity in skills: while the number of active industrial sectors is given by $\sum_{i=1}^{I} \mathbb{1}_{\left[\Omega_{\text{-}i,t\text{-}1} \geq \widetilde{\Omega}_i\right]}$, the number of established skills in the local economy is given by $\sum_{i=1}^{I} \mathbb{1}_{\left[\Omega_{\text{-}i,t\text{-}1} \geq \widetilde{\Omega}_i\right]} \times J_i + \Omega_A$. This connection underlies the mechanics of endogenous structural change. The variety of local skills—which reflects the existing variety of production activities—favors entry into new industrial activities in the next period. In turn, increasing industrial variety implies increasing skills variety, which favors further diversification in subsequent periods.

The following two lemmas establish that the number of previously existing skills in sectors other than i (i.e., $\Omega_{\text{-}i,t\text{-}1}$) has positive effects on expected efficiency in sector i (i.e., $\mathbb{E}(E_{it})$), and that the magnitude of these effects varies with sectoral levels of complexity.

Lemma 1. The elasticity of expected efficiency in sector i with respect to the number of previously existing skills in other sectors is positive: $\eta_{\mathbb{E}(E_{it}),\Omega_{\text{-}i,t\text{-}1}} \equiv \frac{\Delta \mathbb{E}(E_{it})/\mathbb{E}(E_{it})}{\Delta \Omega_{\text{-}i,t\text{-}1}/\Omega_{\text{-}i,t\text{-}1}} > 0$.

Proof. See section B.4.

The intuition behind Lemma 1 is that in a more diverse economic environment (characterized by a higher number of established skills) there is a higher likelihood of finding existing skills that are close to the ones required by any given sector.

Lemma 2 below captures the differential impact of diversity on expected efficiency in complex sectors, which have production chains with more links and thus are more sensitive to the links' average weakness.

Lemma 2. The elasticity of expected efficiency in sector i with respect to the number of previously existing skills in other sectors is increasing in the sector's complexity: $\Delta\eta_{\mathbb{E}(E_{it}),\Omega_{-i,t-1}}/\Delta J_i > 0$.

Proof. See section B.4.

The following two propositions describe how entry into a sector and sectoral employment levels depend on the variety of skills previously established in other sectors.

Proposition 1. (a) The number of previously established skills in sectors other than i has a weakly positive effect on entry into sector i: $\Delta\mathbb{1}_{\left[\Omega_{-i,t-1}\geq\tilde{\Omega}_i\right]}/\Delta\Omega_{-i,t-1} \geq 0$. (b) The elasticity of expected employment in active sector i with respect to the number of previously established skills in other sectors is positive: $\eta_{\mathbb{E}(L^*_{it}),\Omega_{-i,t-1}} \equiv \frac{\Delta\mathbb{E}(L^*_{it})/\mathbb{E}(L^*_{it})}{\Delta\Omega_{-i,t-1}/\Omega_{-i,t-1}} > 0$.

Proof. (a) See section B.4. (b) Since $\mathbb{E}(L^*_{it})$ is a linear function of $\mathbb{E}(E_{it})$, we have that $\eta_{\mathbb{E}(L^*_{it}),\Omega_{-i,t-1}} = \eta_{\mathbb{E}(E_{it}),\Omega_{-i,t-1}}$. Thus, Proposition 1 follows directly from Lemma 1. □

Proposition 2. The elasticity of expected employment in active sector i with respect to the number of previously existing skills in other sectors is increasing in the sector's complexity: $\Delta\eta_{\mathbb{E}(L^*_{it}),\Omega_{-i,t-1}}/\Delta J_i > 0$.

Proof. Since $\eta_{\mathbb{E}(L^*_{it}),\Omega_{-i,t-1}} = \eta_{\mathbb{E}(E_{it}),\Omega_{-i,t-1}}$, Proposition 2 follows directly from Lemma 2. □

Given that $\Delta\Omega_{-i,t-1}/\Delta\Omega_A > 0$, Proposition 1 implies that agricultural diversity has positive effects on entry and expected employment for any industrial sector i (i.e., $\eta_{\mathbb{E}(L^*_{it}),\Omega_A} \equiv \frac{\Delta\mathbb{E}(L^*_{it})/\mathbb{E}(L^*_{it})}{\Delta\Omega_A/\Omega_A} > 0$ and $\Delta\mathbb{1}_{\left[\Omega_{-i,t-1}\geq\tilde{\Omega}_i\right]}/\Delta\Omega_A \geq 0$), as well as differentially positive effects in complex sectors ($\Delta\eta_{\mathbb{E}(L^*_{it}),\Omega_A}/\Delta J_i > 0$). Thus, agricultural diversity, by increasing the variety of local skills, positively affects industrial activities both in the extensive and the intensive margin. Proposition 2 captures the differential effects of diversity in complex activities, which motivates the empirical analysis of section V.C.

The following proposition establishes the positive effects of agricultural diversity on the number of active industrial sectors and total (expected) industrial employment.

Proposition 3. Consider two local economies, s and z, that in a given period $t-1$ are identical in all respects except that s has higher agricultural diversity, so $\Omega_{A,s} > \Omega_{A,z}$. In period t, economy s has a weakly higher number of active industrial sectors and a weakly higher expected value of total industrial employment than economy z: $\sum_{i=1}^{I} \mathbb{1}_{\left[\Omega_{-i,s,t-1} \geq \widetilde{\Omega}_i\right]} \geq \sum_{i=1}^{I} \mathbb{1}_{\left[\Omega_{-i,z,t-1} \geq \widetilde{\Omega}_i\right]}$ and $\mathbb{E}\left(\sum_{i=1}^{I} L_{i,s,t}\right) \geq \mathbb{E}\left(\sum_{i=1}^{I} L_{i,z,t}\right)$.

Proof. See section B.4.

B.3 Long-run Development

In this subsection, I analyze the process of skills formation and structural change, and establish the effects of initial diversity on long-run economic performance.

First, note that the collection of sector-specific thresholds can be arranged in increasing order; this sequence can then be used to define a new index spanning industrial sectors, $q = 1, ..., I$, where sectors with high q have high entry thresholds. If there are sectors with the same entry threshold $\widetilde{\Omega}_i$, the q-index assigns them contiguous integers in arbitrary order. Arranging sectors by their entry thresholds is equivalent to arranging them by timing of entry: sectors with high entry thresholds enter production relatively late, if at all.

The equation for the number of skills at time t can be rewritten using the q-index. This equation, together with the initial condition (with t=0 preceding the onset of industrialization), fully characterizes the evolution of local skills:

$$\Omega_{ct} = \sum_{q=1}^{I} \mathbb{1}_{\left[\Omega_{-q,t-1} \geq \widetilde{\Omega}_q\right]} \times J_q + \Omega_{A,c}$$

$$\Omega_{c0} = \Omega_{A,c}$$

This characterization of the evolution of skills (which determines the evolution of sectoral levels of employment and production) is instrumental to define the *rest points* and the *steady state* of the local economy.

Definition 1. (*Rest point*) Industrial sector $q = m$ (with $m \geq m'$ for any m' such that $\widetilde{\Omega}_{m'} = \widetilde{\Omega}_m$) is a *rest point* of the local economy if $\sum_{q=1}^{m} J_q + \Omega_{A,c} < \widetilde{\Omega}_{m+1}$. In addition, industrial sector $q = I$ is a *rest point*.

When the local economy reaches a rest point, the process of structural change reaches an end. This follows from the definition. If the economy has entered production in all sectors with $q \leq m$ (with sector m having the highest arbitrarily assigned q-index value among sectors with the same entry threshold), then the number of established skills is $\sum_{q=1}^{m} J_q + \Omega^A$. If this is below the threshold required to enter production in sector m+1 (i.e., $\widetilde{\Omega}_{m+1}$), then the process of industrial diversification cannot go beyond sector m. In addition, the process of structural change cannot go beyond sector $q = I$ (the one with the highest entry threshold), since once that sector becomes active there are no inactive sectors left to enter.

A local economy may have more than one rest point, but it is the first one (the rest point with lowest q) that matters, as it defines the *steady state* of the economy.

Definition 2. (*Steady state*) The rest point with the lowest q defines the *steady state* of the local economy. The sector defining the steady state is denoted by q_c^*, and the number of skills in the steady state is $\Omega_c^* = \sum_{q=1}^{q_c^*} J_q + \Omega_{A,c}$.

When the economy enters production in sector q_c^*, the process of structural change concludes. While the economy then continues to grow at a rate given by (exogenous) technological progress in the frontier, endogenous growth through diversification is shut down. The steady state is characterized by a constant growth rate and a stable composition of production.

The next proposition establishes the effects of agricultural diversity on comparative economic performance in the long-run.

Proposition 4. Consider two local economies, s and z, that are identical in all respects except that s has higher agricultural diversity, so $\Omega_{A,s} > \Omega_{A,z}$. In the steady state, economy s has a weakly higher number of active industrial sectors and a higher number of established skills than economy z: $q_s^* \geq q_z^*$ and $\Omega_s^* > \Omega_z^*$.

Proof. See section B.4.

B.4 Proofs

Proof of Lemma 1.

Using the definition of $\eta_{\mathbb{E}(E_{it}),\Omega_{\text{-}i,t\text{-}1}}$ and equation (1), we have that

$$\eta_{\mathbb{E}(E_{it}),\Omega_{\text{-}i,t\text{-}1}} = \frac{\left(\frac{1+\Delta\Omega_{\text{-}i,t\text{-}1}/\Omega_{\text{-}i,t\text{-}1}}{1+\Delta\Omega_{\text{-}i,t\text{-}1}/(\Omega_{\text{-}i,t\text{-}1}+1)}\right)^{J_i} - 1}{\Delta\Omega_{\text{-}i,t\text{-}1}/\Omega_{\text{-}i,t\text{-}1}} \quad .$$

Since $\Delta\Omega_{\text{-}i,t\text{-}1}/(\Omega_{\text{-}i,t\text{-}1}) > \Delta\Omega_{\text{-}i,t\text{-}1}/(\Omega_{\text{-}i,t\text{-}1}+1)$ and $J_i \geq 1$, we have $\left(\frac{1+\Delta\Omega_{\text{-}i,t\text{-}1}/\Omega_{\text{-}i,t\text{-}1}}{1+\Delta\Omega_{\text{-}i,t\text{-}1}/(\Omega_{\text{-}i,t\text{-}1}+1)}\right)^{J_i} > 1$, and thus $\eta_{\mathbb{E}(E_{it}),\Omega_{\text{-}i,t\text{-}1}} > 0$. □

Proof of Lemma 2.

Using the expression for $\eta_{\mathbb{E}(E_{it}),\Omega_{\text{-}i,t\text{-}1}}$ from the proof of Lemma 1, we have that

$$\frac{\Delta\eta_{\mathbb{E}(E_{it}),\Omega_{\text{-}i,t\text{-}1}}}{\Delta J_i}=\frac{\frac{\left(\frac{1+\Delta\Omega_{\text{-}i,t\text{-}1}/\Omega_{\text{-}i,t\text{-}1}}{1+\Delta\Omega_{\text{-}i,t\text{-}1}/(\Omega_{\text{-}i,t\text{-}1}+1)}\right)^{J_i+\Delta J_i}-\left(\frac{1+\Delta\Omega_{\text{-}i,t\text{-}1}/\Omega_{\text{-}i,t\text{-}1}}{1+\Delta\Omega_{\text{-}i,t\text{-}1}/(\Omega_{\text{-}i,t\text{-}1}+1)}\right)^{J_i}}{\Delta\Omega_{\text{-}i,t\text{-}1}/\Omega_{\text{-}i,t\text{-}1}}}{\Delta J_i}\ .$$

Noting that $\Delta\Omega_{\text{-}i,t\text{-}1}/(\Omega_{\text{-}i,t\text{-}1})>\Delta\Omega_{\text{-}i,t\text{-}1}/(\Omega_{\text{-}i,t\text{-}1}+1)$ and $J_i\geq 0$, and also that $\Delta J_i\geq 1$, we have that $\left(\frac{1+\Delta\Omega_{\text{-}i,t\text{-}1}/\Omega_{\text{-}i,t\text{-}1}}{1+\Delta\Omega_{\text{-}i,t\text{-}1}/(\Omega_{\text{-}i,t\text{-}1}+1)}\right)^{J_i+\Delta J_i}>\left(\frac{1+\Delta\Omega_{\text{-}i,t\text{-}1}/\Omega_{\text{-}i,t\text{-}1}}{1+\Delta\Omega_{\text{-}i,t\text{-}1}/(\Omega_{\text{-}i,t\text{-}1}+1)}\right)^{J_i}$, and thus $\frac{\Delta\eta_{\mathbb{E}(E_{it}),\Omega_{\text{-}i,t\text{-}1}}}{\Delta J_i}>0$. □

Proof of Proposition 1(a).

For $\Delta\Omega_{\text{-}i,t\text{-}1}>0$, if $\Omega_{\text{-}i,t\text{-}1}\geq\widetilde{\Omega}_i$, then $\Omega_{\text{-}i,t\text{-}1}+\Delta\Omega_{\text{-}i,t\text{-}1}\geq\widetilde{\Omega}_i$; thus, if $\mathbb{1}_{\left[\Omega_{\text{-}i,t\text{-}1}\geq\widetilde{\Omega}_i\right]}=1$, then $\mathbb{1}_{\left[\Omega_{\text{-}i,t\text{-}1}+\Delta\Omega_{\text{-}i,t\text{-}1}\geq\widetilde{\Omega}_i\right]}=1$. This implies that $\frac{\Delta\mathbb{1}_{\left[\Omega_{\text{-}i,t\text{-}1}\geq\widetilde{\Omega}_i\right]}}{\Delta\Omega_{\text{-}i,t\text{-}1}}=\frac{\mathbb{1}_{\left[\Omega_{\text{-}i,t\text{-}1}+\Delta\Omega_{\text{-}i,t\text{-}1}\geq\widetilde{\Omega}_i\right]}-\mathbb{1}_{\left[\Omega_{\text{-}i,t\text{-}1}\geq\widetilde{\Omega}_i\right]}}{\Delta\Omega_{\text{-}i,t\text{-}1}}\geq 0$. The inequality is strict in cases where $\Delta\Omega_{\text{-}i,t\text{-}1}>\widetilde{\Omega}_i-\Omega_{\text{-}i,t\text{-}1}>0$. Using the same logic it is straightforward to show that for $\Delta\Omega_{\text{-}i,t\text{-}1}<0$, we have $\Delta\mathbb{1}_{\left[\Omega_{\text{-}i,t\text{-}1}\geq\widetilde{\Omega}_i\right]}\leq 0$. □

Proof of Proposition 3.

Since economies s and z are identical in all respects except that $\Omega_{A,s}>\Omega_{A,z}$, then for each sector i we have that $\Omega_{\text{-}i,s,t\text{-}1}>\Omega_{\text{-}i,z,t\text{-}1}$ and thus $\mathbb{1}_{\left[\Omega_{\text{-}i,s,t\text{-}1}\geq\widetilde{\Omega}_i\right]}\geq\mathbb{1}_{\left[\Omega_{\text{-}i,z,t\text{-}1}\geq\widetilde{\Omega}_i\right]}$. This implies that $\sum_{i=1}^{I}\mathbb{1}_{\left[\Omega_{\text{-}i,s,t\text{-}1}\geq\widetilde{\Omega}_i\right]}\geq\sum_{i=1}^{I}\mathbb{1}_{\left[\Omega_{\text{-}i,z,t\text{-}1}\geq\widetilde{\Omega}_i\right]}$. In regards to total expected industrial employment, note first that it can be expressed as $\mathbb{E}\left(\sum_{i=1}^{I}L_{i,c,t}\right)=\sum_{i=1}^{I}\mathbb{E}\left(L_{i,c,t}\right)=\sum_{i=1}^{I}\mathbb{1}_{\left[\Omega_{\text{-}i,c,t\text{-}1}\geq\widetilde{\Omega}_i\right]}\times\mathbb{E}\left(L^*_{i,c,t}\right)$. Next, note that each of the two factors in every term of this summation is (at least weakly) higher in economy s: $\mathbb{1}_{\left[\Omega_{\text{-}i,s,t\text{-}1}\geq\widetilde{\Omega}_i\right]}\geq\mathbb{1}_{\left[\Omega_{\text{-}i,z,t\text{-}1}\geq\widetilde{\Omega}_i\right]}$ for all i as shown above; and given that $\eta_{\mathbb{E}(L^*_{it}),\Omega_A}>0$, the inequality $\Omega_{A,s}>\Omega_{A,z}$ also implies that $\mathbb{E}\left(L^*_{i,s,t}\right)>\mathbb{E}\left(L^*_{i,z,t}\right)$. Thus, we have that $\mathbb{E}\left(\sum_{i=1}^{I}L_{i,s,t}\right)\geq\mathbb{E}\left(\sum_{i=1}^{I}L_{i,z,t}\right)$ □

Proof of Proposition 4.

If m is a rest point for economy s, this means that $\sum_{q=1}^{m}J_q+\Omega_{A,s}<\widetilde{\Omega}_{m+1}$. And since $\Omega_{A,z}<\Omega_{A,s}$, then $\sum_{q=1}^{m}J_q+\Omega_{A,z}<\widetilde{\Omega}_{m+1}$, which means that m is a also rest point for economy z. Since any rest point for economy s is also a rest point for economy z (which may have additional rest points), then the sector defining the steady state of economy s (the rest point with lower q) must be at least as high (in terms of q) as the one for economy z, i.e. $q^*_s\geq q^*_z$. Thus, we have that $\Omega^*_s=\sum_{q=0}^{q^*_s}J_q+\Omega_{A,s}>\sum_{q=0}^{q^*_z}J_q+\Omega_{A,z}=\Omega^*_z$ □

Appendix C. Other channels

C.1 Agricultural Productivity

The positive effect of early agricultural diversity on industrialization may have been generated, at least partly, through an effect of agricultural diversity on agricultural productivity. Maybe agricultural diversity increased agricultural productivity, which in turn pushed labor out of agriculture? Or maybe agricultural diversity negatively affected agricultural productivity, and this was conducive to industrialization? For agricultural productivity to be a channel underlying the observed empirical patterns, the effect of agricultural diversity on agricultural productivity and the effect of the latter on industrialization need to be significant and have the same sign. I empirically assess the two links below, and find that the evidence does not support the relevance of this channel.

How would agricultural diversity affect agricultural productivity? A positive effect could operate through economies of scope in agricultural production (Paul and Nehring, 2005; Kim et al., 2012). Complementarities or positive externalities across products may arise from the beneficial use of byproducts (e.g., manure from livestock used as fertilizer) or from more efficient use of labor (e.g., if labor requirements for different crops have heterogeneous seasonal patterns). Diversity may also help to preserve soil quality over time (Russelle et al., 2007). Moreover, it could broaden the knowledge base and thus foster agricultural innovation and technology adoption. On the other hand, if agricultural diversity implies foregoing gains from specialization based on comparative advantage or scale economies, it could have negative effects on productivity.

In turn, agricultural productivity may affect industrialization in either direction, through various mechanisms. On the one hand, higher productivity in agriculture can release labor to be employed in manufacturing; it also means cheaper food for workers and cheaper inputs for firms; it creates resources for investment, which can be channeled towards industrial capital formation; and it means higher purchasing power and thus higher demand for local manufacturing production (Johnston and Mellor, 1961). On the other hand, Matsuyama (1992) demonstrates that in open economies agricultural productivity can have a negative effect on industrial growth by shifting comparative advantage in favor of agriculture (naturally, high transport costs would hold back this effect).

Throughout Appendix C (as in section V of the paper), I report OLS and IV estimates for three specifications, controlling for (i) state fixed effects, (ii) state fixed effects and geo-climatic conditions, and (iii) state fixed effects, geo-climatic conditions, crop-specific controls, and socio-economic conditions. Panel A of Table C.1 shows estimates of the effect of agricultural diversity in 1860 on farm output per improved acre (in logs) ten years later, right around the onset of the Second Industrial Revolution. Panel B displays estimates of the effect of this measure of agricultural productivity on the share of population employed in manufacturing in 1900, the measure of industrialization used in the main analysis. The IV estimates of the effects of agricultural productivity use the first principal component of the FAO-GAEZ normalized crop-specific attainable yields as an IV (in these estimations I exclude the measures of potential land productivity from the set of geo-climatic controls). The results do not offer support for the relevance of this channel: I do not find robust results indicating an effect of agricultural diversity on agricultural productivity nor an effect of the latter on industrialization.

TABLE C.1. AG. DIVERSITY, AG. PRODUCTIVITY, AND INDUSTRIALIZATION

	Specification 1		Specification 2		Specification 3	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. *Dependent variable: Ln Farm Productivity, 1870*						
Ag. Diversity$_{1860}$	-0.438	-0.185	-0.286	0.104	-0.278	0.195
	(0.229)	(0.315)	(0.219)	(0.363)	(0.166)	(0.539)
R^2	0.377	0.374	0.409	0.403	0.490	0.483
Panel B. *Dependent variable: Share of population in manufacturing, 1900*						
Ln Farm Productivity$_{1870}$	0.0136	-0.0478	0.0130	0.0197	-0.00137	0.0155
	(0.00240)	(0.0519)	(0.00237)	(0.0170)	(0.00223)	(0.0206)
R^2	0.449	0.148	0.466	0.462	0.613	0.549
State FE	Y	Y	Y	Y	Y	Y
Geo-climatic controls	N	N	Y	Y	Y	Y
Crop-specific controls	N	N	N	N	Y	Y
Socio-economic controls	N	N	N	N	Y	Y
Observations	1,819	1,819	1,819	1,819	1,819	1,819

Notes: See Appendix A.1 for variable definitions and sources. In the regressions reported in Panel B, land productivity measures are not included in the set of geo-climatic controls; the IV estimations use the first principal component of the FAO-GAEZ normalized crop-specific attainable yields is used as IV. The sample is reduced to 1,819 as 2 counties with no farm output in 1870 drop out. The means of the dependent variables in panels A and B are 2.56 and 0.034, respectively. Robust standard errors clustered on 60-square-mile grid squares are reported in parentheses.

C.2 Volatility, Risk and Local Financial Development

Positive effects of agricultural diversity could arise from reduced risk and volatility, as suggested by some of the contributions reviewed in section I of the paper (Acemoglu and Zilibotti, 1997; Koren and Tenreyro, 2013). Diversification dampens the direct impact of negative product-specific shocks and also facilitates substitution away from negatively affected products. Olmstead and Rhode (2008) document various negative shocks affecting specific agricultural products during the period under consideration, highlighting the potential relevance of this mechanism. Moreover, if agents are risk averse, being able to reduce risk and volatility by diversifying agricultural production may be a precondition for carrying out risky projects with high returns in the manufacturing sector. Note, however, that reduced agricultural volatility makes industrial investments comparatively less attractive, and thus an effect in the opposite direction is also possible.

Beyond the effects mentioned above, lower levels of risk afforded by diversity could affect local financial development. Insofar as it allows local banks to reduce risk exposure by funding a wide array of imperfectly correlated projects, diversity may increase credit supply (Ramcharan, 2010b). On the other hand, people in places that are well-suited to limit volatility through diversification may have lower demand for financial services. Finally, in addition to affecting local financial institutions (positively through supply or negatively through demand), diversity could influence social norms: higher volatility may foster mutual insurance arrangements and thus help to build trust (Durante and Buggle, 2016). In turn, local financial development and trust may affect economic development through channels other than risk management.

To assess whether agricultural diversity fostered industrialization through reduced volatility, I construct a measure of predicted volatility in the value of agricultural production by combining the initial county-level production mix and the year-to-year evolution of national prices between 1867 and 1900. More precisely, I calculate a predicted price index for a county's agricultural production in year t as $P^{\mathrm{a}}_{ct} = \sum_i \theta_{ic} p_{it}$, where the θ_{ic}'s reflect the county's agricultural production mix in 1860, and p_{it} is the national price of product i in period t (with p_{i1867} normalized to 1 for all i). I then calculate the rate of change $\widehat{P}^{\mathrm{a}}_{ct} = (P^{\mathrm{a}}_{ct} - P^{\mathrm{a}}_{ct-1})/P^{\mathrm{a}}_{ct-1}$ for each year, as well as its average and standard deviation over the 1867-1900 period, $Avg.\widehat{P}^{\mathrm{a}}_{ct}$ and $Std.Dev.(\widehat{P}^{\mathrm{a}}_{ct})$.[9] H

[9] Annual price data from 1867 to 1900 are available for 15 products that account for over 93.5% of total agricultural output in 1860 in my sample (see Appendix A.1 for details). Only products with available price data are considered in the calculation of P^{a}_{ct}; the θ_{ic}'s are computed with the restricted set of products so that they add up to 1. The results are qualitatively similar in a reduced sample of 1,626 counties for which over 90% of agricultural production in each county corresponds to the 15 products with available price

Constructed in this way, $\widehat{P}^{\mathrm{a}}_{ct}$ captures the predicted effect of national-level price changes in a county's agricultural production value given the local production mix, and $Std.Dev.(\widehat{P}^{\mathrm{a}}_{ct})$ captures the volatility of predicted agricultural production value. While county-level volatility naturally depends on the specific local production mix and the covariances of national-level price changes, $Std.Dev.(\widehat{P}^{\mathrm{a}}_{ct})$ has a strong negative association with agricultural diversity (the correlation coefficient in the sample is -0.37).

The relevance of the volatility channel can be assessed by comparing estimates of the effects of agricultural diversity in 1860 on industrialization in 1900 obtained with and without controlling for $Std.Dev.(\widehat{P}^{\mathrm{a}}_{ct})$ (together with $Avg.\widehat{P}^{\mathrm{a}}_{ct}$ to avoid potential omitted variable bias). If diversity positively affected industrialization by reducing volatility, $Std.Dev.(\widehat{P}^{\mathrm{a}}_{ct})$ would have a negative and significant coefficient, and its inclusion would reduce the coefficient on agricultural diversity, possibly making it insignificant (if this channel was the only relevant one). The results of the estimations, displayed in Table C.2, are not in line with these predictions. The estimated effect of $St.Dev.(\widehat{P}^{\mathrm{a}}_{ct})$ is not significant and the estimated coefficient on 1860 agricultural diversity remains significant and of similar magnitude.

I can also examine whether diversity affected financial development. Table C.3 presents estimates of the effects of agricultural diversity in 1860 on county-level bank density (the number of banks per capita) in 1920, the measure considered by Rajan and Ramcharan (2011) in their study of local financial development in this period. The results do no show significant causal effects.

C.3 Land Concentration and Local Institutions

Agricultural diversity may have affected the manufacturing sector by shaping the distribution of land ownership. If there are increasing returns to scale at the product-level (e.g., fixed costs due to crop-specific capital or skills), then places with low potential diversity (e.g, with very high relative productivity for a single product) may be more favorable for the development of large-scale farms. In addition, if economies of scope (the benefits of diversification) at the farm-level are higher for small farms (Chavas and Aliber, 1993), then places with high potential diversity would be favorable to small farms. On the other hand, if different crops are characterized by different optimal production scales, then diversity could be positively associated with inequality in farm size.

In turn, the presence of large landowners may retard the emergence of human capital promoting institutions (Galor et al., 2009) and/or hinder local financial development (Rajan

data. Results are also qualitatively similar if I consider the standard deviation of P^{a}_{ct} instead of the standard deviation of $\hat{P}^{\mathrm{a}}_{ct}$.

and Ramcharan, 2011), thus negatively affecting the process of industrialization. Galor et al. (2009) provide a panel data analysis at the U.S. state-level from 1880 to 1940 showing that concentration in land ownership had a significant adverse effect on educational expenditures; this was a period characterized by a massive expansion of secondary education, which—as suggested by the model presented in their paper—was key for industrialization. Ramcharan (2010a) and Vollrath (2013) provide evidence in the same direction from U.S. county-level data for the same period.

Table C.2. Assessing the Risk and Volatility Channel

	Dependent variable: Share of population in manufacturing, 1900					
	Specification 1		Specification 2		Specification 3	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. OLS estimates						
Ag. Diversity$_{1860}$	0.0358	0.0387	0.0404	0.0440	0.0333	0.0341
	(0.00949)	(0.0107)	(0.00919)	(0.0109)	(0.00825)	(0.0117)
$Std.Dev.(\widehat{P}^{\mathrm{a}}_{ct})$		-0.0285		0.00719		0.0238
		(0.0817)		(0.0808)		(0.0751)
$Avg.\widehat{P}^{\mathrm{a}}_{ct}$		0.484		0.263		-0.143
		(0.586)		(0.563)		(0.638)
R^2	0.439	0.440	0.461	0.461	0.618	0.618
Panel B. IV estimates						
Ag. Diversity$_{1860}$	0.0719	0.0764	0.0830	0.0890	0.0884	0.111
	(0.0219)	(0.0247)	(0.0213)	(0.0237)	(0.0309)	(0.0435)
$Std.Dev.(\widehat{P}^{\mathrm{a}}_{ct})$		0.0510		0.103		0.206
		(0.0897)		(0.0911)		(0.130)
$Avg.\widehat{P}^{\mathrm{a}}_{ct}$		0.499		0.249		0.115
		(0.582)		(0.570)		(0.661)
R^2	0.433	0.434	0.452	0.453	0.607	0.604
State FE	Y	Y	Y	Y	Y	Y
Geo-climatic controls	N	N	Y	Y	Y	Y
Crop-specific controls	N	N	N	N	Y	Y
Socio-economic controls	N	N	N	N	Y	Y
Observations	1,821	1,821	1,821	1,821	1,821	1,821

Notes: $\bar{G}p^{\mathrm{a}}_{c,t}$ is the annual percentage change of $p^{\mathrm{a}}_{c,t} = \sum_i \hat{\theta}_{ic} p_{i,t}$, a predictor of the value of agricultural output constructed with predicted shares for 1860 and subsequent national prices. $Std.Dev.(Gp^{\mathrm{a}}_{c,t})$ is its standard deviation. See Appendix A for other variable definitions and sources. The mean of the share of population in manufacturing in 1900 is 0.034. Robust standard errors clustered on 60-square-mile grid squares are reported in parentheses.

Table C.3. Effects of Agricultural Diversity on Local Financial Development

	Dependent variable: Bank density, 1920					
	Specification 1		Specification 2		Specification 3	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Ag. Diversity$_{1860}$	-00424	0.173	-0.0815	0.0652	-0.0890	-0.0143
	(0.0544)	(0.118)	(0.0490)	(0.109)	(0.0554)	(0.166)
State FE	Y	Y	Y	Y	Y	Y
Geo-climatic controls	N	N	Y	Y	Y	Y
Crop-specific controls	N	N	N	N	Y	Y
Socio-economic controls	N	N	N	N	Y	Y
Observations	1,821	1,821	1,821	1,821	1,821	1,821
R^2	0.622	0.616	0.649	0.646	0.691	0.691

Notes: See Appendix A.1 for variable definitions and sources. The mean of bank density in 1920 is 0.38. Robust standard errors clustered on 60-square-mile grid squares are reported in parentheses.

Rajan and Ramcharan (2011) argue that landed elites may hinder the development of local banks to maintain their power. Their paper shows that in the early 20th century U.S., counties with higher land inequality had fewer banks per capita and less access to credit. Even if large landowners did not obstruct financial development, high land inequality could imply that many prospective borrowers had limited access to credit because of insufficient collateral (e.g., Chakraborty and Ray, 2007).[10]

Did agricultural diversity lower land concentration? Panel A of Table C.4 shows estimates of the effects of agricultural diversity in 1860 on the share of farmland corresponding to the top 10% largest farms ten years later, around the onset of the Second Industrial Revolution. The results do not indicate a significant causal effect of agricultural diversity on land concentration.

I can also assess whether agricultural diversity affected local school expenditures and/or financial development, the outcomes that would be influenced by the presence of powerful landed elites according to the theories discussed above. Table C.3 (already discussed in section C.2) shows that there were no significant effects of early agricultural diversity on bank density in 1920. Likewise, using data on educational expenditures in 1890 from Rhode and

[10] Adamopoulos (2008) also argues that land concentration can hinder industrialization insofar as landed elites can influence policies to protect their rents. In his model, which is used to explain the divergence between Argentina and Canada, the policy that blocks industrialization is an import tariff on intermediate inputs required by manufacturing. Naturally, this mechanism cannot explain divergence across U.S. counties.

Strumpf (2003), I find no evidence that these were significantly affected by 1860 agricultural diversity, as indicated by the results displayed in Panel B of Table C.4. Thus, I conclude that the evidence does not support the relevance of this channel.

Table C.4. Effects of Ag. Diversity on Land Concentration and Public Schooling

	Specification 1		Specification 2		Specification 3	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. *Dependent variable: Share of farmland in the top 10% largest farms, 1870*						
Ag. Diversity$_{1860}$	-0.00964	-0.0658	0.0379	0.0301	0.0386	-0.0157
	(0.0271)	(0.0812)	(0.0289)	(0.0884)	(0.0329)	(0.137)
R^2	0.264	0.261	0.308	0.308	0.386	0.384
Observations	1,819	1,819	1,819	1,819	1,819	1,819
Panel B. *Dependent variable: Ln School expenditures per capita, 1890*						
Ag. Diversity$_{1860}$	0.150	-0.289	0.0796	-0.603	0.107	-0.817
	(0.107)	(0.400)	(0.0969)	(0.485)	(0.101)	(0.593)
R^2	0.797	0.794	0.811	0.805	0.822	0.814
Observations	1,809	1,809	1,809	1,809	1,809	1,809
State FE	Y	Y	Y	Y	Y	Y
Geo-climatic controls	N	N	Y	Y	Y	Y
Crop-specific controls	N	N	N	N	Y	Y
Socio-economic controls	N	N	N	N	Y	Y

Notes: See Appendix A.1 for variable definitions and sources. The means of the dependent variables in Panels A and B are 0.83 and 0.23, respectively. Robust standard errors clustered on 60-square-mile grid squares are reported in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

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