Agricultural Diversity, Structural Change and Long-run Development: Evidence from US Counties*

Martin Fiszbein§

January 8, 2015

Abstract

This paper examines the role of agricultural diversity in the process of economic development. Using data from US counties and exploiting exogenous variation in agricultural production patterns induced by climatic features, I find a sizable positive impact of mid-19th century agricultural diversity on contemporary income per capita. The positive effects emerged over the course of the Second Industrial Revolution, when early agricultural diversity boosted the relative size and productivity of the manufacturing sector. An assessment of mechanisms suggests that these effects operated through increased manufacturing diversification, formation of novel skills, and technological progress. In line with these results, I find differential effects of agricultural diversity on skill- and knowledge-intensive industrial activities. To sharpen the interpretation of the findings, I propose a multi-sector growth model that highlights the interconnected roles of complementarities and cross-sector spillovers in the mechanics of structural change, and explains why agricultural diversity can have long-run effects that unfold over time. (*JEL* O11, O41, N11, N51)

*I am grateful to Oded Galor, Stelios Michalopoulos and David Weil for their invaluable guidance. I also wish to acknowledge useful comments and suggestions by Nathaniel Baum-Snow, Joaquin Blaum, Pedro Dal Bo, Emilio Depetris-Chauvin, Jonathan Eaton, Andrew Foster, Raphael Franck, Martin Guzman, Ricardo Hausmann, Vernon Henderson, Richard Hornbeck, Peter Howitt, Marc Klemp, Cynthia Mei Balloch, Sriniketh Nagavarapu, Suresh Naidu, Omer Ozak, Louis Putterman, Lucia Sanchez, Matthew Turner, Alex Whalley, and participants at NEUDC 2014 (Boston University), Harvard CID's growth seminar, Brown's Macroeconomics Seminar, EconCon 2014 (Princeton University), Brown's Growth Conference 2014, and NEUDC 2013 (Harvard Kennedy School of Government).

§Brown University, Department of Economics, 64 Waterman Street, Providence, RI 02912, USA (email: martin_fiszbein@brown.edu).

1 Introduction

Differences in contemporary levels of development observed across countries and regions are partly explained by variation in the timing and scope of transitions from agriculture to industry. These structural transformations, in turn, are influenced by specific features of economies at earlier stages of development. Identifying such features can advance our understanding of comparative development and add to the burgeoning literature that uncovers persistent effects of deeply-rooted factors (see Galor, 2011; Nunn, 2013; Spolaore and Wacziarg, 2013).

Factors affecting long-run growth trajectories include production patterns at early stages of development. The effects of particular specialization patterns have been extensively studied in the literature on economic development (Engerman and Sokoloff, 1997, 2002; Bruhn and Gallego, 2012). Agricultural productivity and land abundance have also attracted considerable interest (Matsuyama, 1992; Gollin et al., 2002; Galiani et al., 2008). Agricultural diversity, in contrast, remains largely unexplored.[1] This paper is the first to examine the effects of diversity in early agricultural production on long-run development.

The impact of agricultural diversity does not have an obvious significance or even an obvious direction. Diversity could affect development in various ways. It could harm development insofar as it implies foregoing economies of scale or knowledge spillovers that operate only at the level of products or narrowly defined sectors. On the other hand, under complementarities between inputs or skills, diversity may yield productivity gains. Moreover, a diverse economic environment may foster skill formation and technological progress. There are also other channels that could account for positive effects of agricultural diversity, such as increased agricultural productivity, reduced volatility, and lower land inequality (which may in turn affect local institutions).

I use a rich dataset of U.S. counties spanning 140 years to assess the effects of agricultural diversity on long-run development. The empirical analysis establishes a strong positive relationship between agricultural diversity in 1860 and contemporary development (measured by per capita income in recent decades). The relationship between diversity and income emerged over the course of the development process. Agricultural diversity in the mid-19th century is positively associated with the share of the population employed in manufacturing and the level of manufacturing productivity around 1900, but not before. This suggests that diversity affected patterns of structural change over the Second Industrial Revolution

[1] Two notable exceptions are the contributions of Michalopoulos (2012) and Fenske (2014), who study the effects of different measures of diversity in geographical endowments on, respectively, ethnolinguistic fragmentation and state centralization in Africa.

(usually dated 1870-1920), during which the US was transformed from a predominantly agricultural economy into the world's leading industrial economy.

The positive association between agricultural diversity in the mid-19th century and later development outcomes holds when controlling for state fixed effects, land productivity, the dominance of specific agricultural products, a host of ecological conditions, distances to major urban centers and waterways, and an extensive set of socio-economic variables. State fixed effects allow me to abstract from the effects of state-level institutions and to mitigate concerns about bias due to unobservable heterogeneity. Still, the correlation could be driven by unobservable factors (e.g., preferences or technology) that vary across counties. To estimate the causal effects of agricultural diversity, I propose an identification strategy that exploits exogenous variation in agricultural production patterns generated by climatic features.

I construct an instrumental variable (IV) for agricultural diversity using climate-based measures of potential productivity for different crops. To do this, I estimate a fractional multinomial logit (FML) model of crop choice in which the shares of each product in total agricultural output are the outcome variables, and the crop-specific productivity measures are explanatory variables. With the predicted shares obtained from this estimation, I compute an index of potential diversity. I then use this index as an IV for actual agricultural diversity, and find positive and significant IV estimates of the effects of agricultural diversity on development outcomes.

After establishing that agricultural diversity had long-term positive effects, I proceed to examine the mechanisms that can potentially account for the observed empirical patterns. The explanation offered in this paper, which emphasizes complementarities, cross-sector spillovers and recombinant learning, is that agricultural diversity can foster broader diversification, skill formation, and technological progress. I find that, once the Second Industrial Revolution was underway, agricultural diversity had positive effects on intermediate variables capturing those channels. Moreover, cross-county cross-industry regressions show a positive differential impact of agricultural diversity on skill-intensive and knowledge-intensive industries, lending further support to the proposed explanation.

To sharpen my interpretation of the findings, I propose a multi-sector endogenous growth model that highlights the interconnected roles of complementarities and cross-sector spillovers in the mechanics of structural change. I consider a small local economy, open to trade and labor flows, with agricultural production and several industrial sectors, each of which may be active or not. Industrial sectors are heterogeneous in their level of complexity, defined as the number of sector-specific production capabilities they require. Capabilities within in each sector are complementary. Within each local economy there are cross-sector spillovers: efficiency in a sector depends on the set of established capabilties in other sectors. In the model, agricultural diversity is determined by exogenous climatic features, and it has a positive impact on industrialization as well as differentially positive effects on relatively complex industrial sectors. These effects unfold over time as local economies go through critical junctures in which the number of productive capabilities originated in agriculture determines whether the process of structural change continues or ceases.

I also consider other channels that could account for the effects of agricultural diversity, and find that the evidence does not support their relevance. First, I examine whether agricultural diversity affected industrialization through an effect on agricultural productivity. The evidence is not consistent with an agricultural productivity channel, thus underscoring the cross-sectoral nature of the impact of agricultural diversity on industrialization. Next, I assess whether agricultural diversification spurred growth by reducing volatility in the value of agricultural production. To do this, I construct a measure of predicted volatility based on the evolution of national prices for different agricultural products and on the product shares predicted by the FML model used to construct the IV. Empirical patterns do not support this mechanism. Finally, I consider political economy channels that may have operated at the local level. I find a negative effect of early agricultural diversity on land concentration, but no evidence of impacts on financial development or education provision.

The results presented in this paper complement recent quantitative studies of US history showing persistent effects of geographical features that are no longer directly relevant (e.g., Bleakley and Lin, 2012; Hornbeck, 2012; Glaeser et al., 2012). More broadly, the findings add to the evidence on how geographic factors have influenced contemporary outcomes by shaping historical trajectories of economic, social, and political development (Diamond, 1997; Acemoglu et al., 2001; Engerman and Sokoloff, 1997, 2002). While highlighting the long-run impact of climate through its influence on agricultural production patterns, my research goes beyond the role of particular crops to uncover the effects of diversity. This focus on diversity provides a distinct addition to the literature on the role of agriculture in the process of development.

This paper also contributes to the literature on diversification and growth (Acemoglu and Zilibotti, 1997; Imbs and Wacziarg, 2003; Koren and Tenreyro, 2013), offering an analysis of different channels in historical perspective and a focus on agriculture that permits a novel identification strategy. The empirical findings provide strong support for the relevance of a set of mechanisms that have attracted considerable attention in urban economics (e.g., Glaeser et al., 1992; Henderson et al., 1995; Combes, 2000). The importance of diversity has implications for the literature on growth and structural change (e.g. Alvarez-Cuadrado and Poschke, 2011; Herrendorf et al., 2013), suggesting that the analysis of linkages and complementarities in models with finer levels of aggregation than standard two- or three-sector frameworks may yield new insights about the development process.

The paper is organized as follows. The next section discusses the literature on diversity and development. The third section presents the data as well as the estimating equation and baseline results from ordinary least squares (OLS) estimation. Section four outlines the instrumental variable strategy and discusses the IV estimates. Section five offers evidence on the mechanisms that account for the long-term effects of agricultural diversity, and section six presents a model capturing those mechanisms. Section seven examines other potential channels. Section eight concludes.

2 Diversity and Development: Theories and Evidence

The relationship between diversity and development has been addressed by a number of theories with contrasting implications about the sign and direction of causality. The ideas discussed in this section, which refer to the relationship between diversity and development for the economy as a whole, are relevant here despite my focus on *agricultural* diversity. Section 5 elaborates on this at length. For the moment, note that the focus on agriculture is not a narrow one—this was the main sector of the US economy in the mid-nineteenth century. Moreover, under the presence of linkages between different agricultural and industrial products, agricultural diversity may be the root of economy-wide diversification.

Long-standing pieces of economic wisdom suggest that specialization, as opposed to diversification, is good for growth. First, any form of increasing returns to scale that operate only within a single sector or product would imply that specialization yields productivity gains. Within urban economics, the idea of localization externalities points to the benefits that firms derive from being co-located with other firms in the same sector. Also prominent among the theoretical underpinnings of arguments for specialization is the principle of comparative advantage. Trade theory posits that increased trade openness or reduced transport costs foster specialization and also increase income.[2] Finally, a cursory consideration of modern portfolio theory might also suggest that growth is diminished by diversification insofar as—with the purpose of attenuating risk—it reduces expected returns.

[2] This prediction arises from models in the Hecksher-Ohlin tradition as well as from Ricardian models with a continuum of goods (Dornbusch et al., 1977; Eaton and Kortum, 2002), where a reduction in trade costs shrinks the range of goods produced and simultaneously increases income. But note that in trade theory it is not specialization which has a causal effect on income but a third variable (e.g., transport costs) which determines both. Moreover, diversification at the macroeconomic level would only be detrimental insofar as there are deviations from the comparative advantage of production units, which may be heterogeneous in their relative productivities for different products. These nuances are not always considered in policy discussions.

In contrast, there are theories that imply a positive relationship between diversity and development. A basic idea pointing in this direction is that under imperfect substitutability between inputs (or skills, or technologies), increasing the diversity of inputs employed in production leads to efficiency gains. This property—analogous to "love of variety" in consumption—can be captured by CES (constant elasticity of substitution) production functions, as in endogenous growth models with expanding varieties *à la* Romer (1990) and New Economic Geography models *à la* Krugman (1991). Strong complementarities between production tasks are the essential element of the O-ring theory of development proposed by Kremer (1993), which higlights that a chain is only as strong as its weakest link. In a recent contribution, Jones (2011) provides insights about the properties of CES productions functions in connection with the role of linkages and complementarities in development.

The relationship between diversity and productivity may go beyond the static relationship implied by production functions with imperfect substitutability. In this paper, I emphasize the dynamic effects of diversity. Going back to Jacobs (1969), the idea of "Jacobs externalities" (connected with urbanization economies, specially those operating through increased flows of knowledge) is that diversity can foster innovation and adoption of new technologies. A set of related ideas sheds light on the nature of this effect. Schmookler (1966) hints at the importance of cross-sector technological spillovers (later documented by Scherer, 1982) and recombinant technological progress (the generation of new ideas as recombinations of older ones, already noted by Usher, 1929, and Schumpeter, 1934). Rosenberg (1979) emphasizes interdepencies between technologies and discusses a number of cases that illustrate their importance in American economic history.

Recombinant technological progress was incorporated in a growth model in a seminal contribution by Weitzman (1998). Van den Bergh (2008) and Zeppini and Van den Bergh (2013) develop a simple framework in which increasing returns to scale in each investment option tend to induce specialization, but on the other hand diversity facilitates recombinant innovations and can thus be efficient in the long-run. Berliant and Fujita (2008, 2011) build an endogenous growth model with expanding varieties that captures the role of knowledge diversity within R&D teams in the dynamics of knowledge creation. Akcigit et al. (2013) advance a novel model of recombinant growth that matches a number of stylized facts documented with a newly-compiled large database of US patents.

While the literature usually emphasizes innovation, the positive impact of diversity could operate through enhanced technology adoption and adaptation (Cohen and Levinthal, 1990). Duranton and Puga (2001) build a model in which diversified cities, characterized by a broad range of intermediate inputs and skills, allow an entrepreneur with a new project to find the ideal productive process. In a model developed by Helsley and Strange (2002), the diversity of input suppliers reduces the cost of bringing new ideas to fruition. Hausmann and Hidalgo (2011) emphasize diversity in productive capabilities (e.g., specific skills): if each product requires a set of capabilities and there are overlaps between capability sets for different products, then diversification would entail a higher return to acquiring new capabilities (that complement previously existing ones) and thus induce faster growth.

Besides all the contributions pointing to the positive effects of diversity arising from complementarities, cross-fertilization and recombination of ideas, there are theories pointing to a substantive role of risk and volatility. In the model advanced by Acemoglu and Zilibotti (1997), risky projects with high returns are only carried out when economies can enter a wide array of projects (sectors); thus, higher diversification goes hand in hand with a higher expected rate of return. A somewhat related theory is proposed by Koren and Tenreyro (2013), who emphasize that diversification dampens the adverse effects of product-specific negative shocks by limiting the direct impact of negative product-specific shocks and facilitating substitution away from negatively affected products.

Finally, in addition to theories that predict a causal effect of diversity on development or a relationship between the two driven by a third factor, there are reasons to expect causality going from development to diversification. If increases in income change the composition of consumption bundles (e.g., Engel's law) and the composition of demand affects production patterns, then diversification and development would be connected through an entirely different channel, with a direction of causality opposite to that of theories discussed above.

Given the multiple forces that may be involved in the relationship between diversity and development, it may not be not surprising that empirical studies have not produced conclusive evidence. The effects of diversity have been most extensively studied in the urban economics literature.[3] Although many studies find positive and significant correlations between diversity and economic performance, this empirical pattern is not fully robust, and there is no clear evidence of the relevance of Jacobs externalities *vis a vis* localization externalities.[4] Moreover, identification challenges have not been adequately addressed. While recent contributions have made significant progress in the identification of agglomeration economies (see Combes et al., 2011), advances focusing on the causal effects of diversity have been less auspicious.

[3]Within the macro-development literature, Imbs and Wacziarg (2003) show that at the country-level diversification follows an inverted U-shaped curve in relation to income. Imbs et al. (2012) confirm this pattern and interpret it as driven by increases in trade in two distinct stages of integration (first between regions and then between countries, with opposite effects on country-level diversification).

[4]A comprehensive review of 67 studies is provided by Beaudry and Schiffauerova (2009). An interesting observation in this review, to which I return in section 5.3, is that the positive effects of diversity appear to be more relevant in high-tech sectors, where cross-fertilization and spillovers are more important.

3 Agricultural Diversity and Development: A First Look

3.1 Data

Historical data on county-level agricultural production, manufacturing employment, value added and wages, several socio-economic variables, employment microdata, as well as personal income and population data are compiled from various sources, including the US Census Bureau, the Minnesota Population Center (2011), Haines and ICPSR (2010), and Ruggles et al. (2010). Full details are provided in appendix A.

The units of observation throughout the paper are US counties as defined in 1860. I drop from the sample all Western states (most of which were still territories and had only started to be partitioned into counties), as well as Dakota Territory, Kansas Territory, Nebraska Territory and Indian Territory (later Oklahoma). Some other counties are dropped because of missing data. For the remaining 1,821 counties (which represented over 97% of national population at the time), I adjust the data to take into account border changes in order to have consistent units of observation across time periods, following a procedure explained in appendix A.

In 1860, over 55% of the labor force was employed in agricultural production, which accounted for around 45% of total output in the US economy (Weiss, 1992). Within my sample of 1,821 counties, over 80% of the population lived in rural areas. Three out of four of these counties did not have any urban population. Rural areas had some industrial production, but the bulk of manufacturing employment was concentrated in major urban centers (25 counties accounted for over half of total manufacturing employment in the sample). As discussed below, agricultural production patterns at this early stage of development had a critical role in shaping the paths of structural change over the Second Industrial Revolution.

To study the role of early agricultural diversity I use detailed data on agricultural activities. The 1860 Census provides production data for 36 products composing agricultural output, which I use in combination with historical state-level price data from Atack and Bateman (1987) and Craig (1993). Table 1 reports the sample average and maximum percentages of county-level agricultural production for each of these products, as well as the percentage of counties in which each product was dominant and the percentage in which it represented over 50% of agricultural output. As can be seen, even marginal products represent large percentages of agricultural output in some counties (e.g., rice represented less 0.3% of agricultural output in the sample but over 86% in Georgetown, South Carolina).

Using these data I calculate a measure of agricultural diversity as 1 minus a Hirschman-Herfindahl index of the shares of each product in total agricultural output (designated as θ_i, with $i = 1, 2, ..., 36$), so the index for each county c is Agri.Diversity$_c = 1 - \sum_i \theta_{ic}^2$. As can be seen in Figure 1, agricultural diversity in 1860 was high in the Northeast and Midwest, but also in the Southeastern seaboard, along the Appalachian Mountains, and in Northern Texas. Beyond regional disparities, agricultural diversity shows significant variation within states, which is important for identification of its effects.

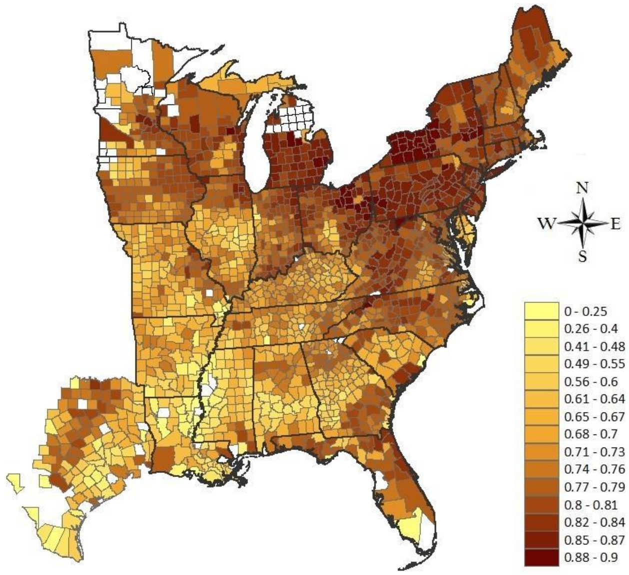
Table 1. Agricultural Production Data

Product	% of Agri.Output		% of Counties		Product	% of Agri.Output		% of Counties	
	Mean	Max	Dominant	>50%		Mean	Max	Dominant	>50%
Corn	23.80	98.89	43.73	11.28	Barley	0.44	10.54	0.00	0.00
Ginned cotton	16.03	94.11	20.08	13.86	Clover seed	0.30	12.93	0.00	0.00
Animals slaughtered	13.08	95.16	04.35	05.50	Rice	0.27	86.38	0.51	0.28
Hay	11.86	73.97	17.22	01.65	Dew-rotted hemp	0.26	64.86	0.55	0.55
Wheat	10.39	92.86	08.42	00.44	Cane molasses	0.25	19.58	0.00	0.00
Butter	04.22	25.36	00.66	00.00	Sorghum molasses	0.25	07.19	0.00	0.00
Oats	03.92	98.89	00.66	00.00	Honey	0.23	08.41	0.11	0.00
Irish potatoes	03.10	59.87	00.77	00.11	Maple sugar	0.22	36.26	0.00	0.00
Tobacco	02.34	57.27	02.59	01.65	Hops	0.17	19.51	0.00	0.00
Sweet potatoes	01.26	30.15	00.22	00.00	Grass seed	0.16	09.39	0.00	0.00
Orchards	01.18	24.18	00.00	00.00	Hemp (other)	0.09	22.04	0.00	0.00
Cane Sugar	01.15	88.43	00.77	00.66	Maple molasses	0.06	07.43	0.00	0.00
Wool	01.01	100.0	00.22	00.22	Flax	0.05	04.83	0.00	0.00
Rye	00.92	13.86	00.00	00.00	Flaxseed	0.04	03.35	0.00	0.00
Market gardens	00.88	94.36	00.66	00.11	Beeswax	0.02	01.03	0.00	0.00
Peas and beans	00.72	22.95	00.00	00.00	Wine	0.02	04.72	0.00	0.00
Cheese	00.70	35.70	00.22	00.00	Water-rotted hemp	0.02	07.17	0.00	0.00
Buckwheat	00.56	15.31	00.00	00.00	Silk cocoon	0.01	02.86	0.00	0.00

Notes: Based on county-level production data from the 1860 Census of Agriculture and state-level price data from Atack and Bateman (1987) and Craig (1993). The statistics for the 36 products that comprise agricultural production are for the sample of 1,821 counties considered in this paper. The first and second columns indicate the average and the maximum of a each product's share in agricultural output; the third column indicates the percentage of counties in which each product had the largest share in agricultural output; the fourth column shows the percentage of counties in which each product represented over 50% of agricultural output.

As this paper shows, mid-19th century agricultural diversity had long-run effects on development that can be traced back to the timing and scope of counties' structural transformation during the Second Industrial Revolution. The average county-level share of population in manufacturing more than doubled from 1860 to 1900, but there was wide variation in industrial performance across counties. While the importance in manufacturing of large industrial urban centers peaked by 1870 (their subsequent growth was led by services), small local economies had an important role in the American industrial takeoff starting in the late 19th century (Meyer, 1989; Page and Walker, 1991). Some counties with little or no manufacturing production in 1860 became thriving mid-sized industrial localities by the early 20th century. Among the counties with zero manufacturing production in 1860 (about 11%

Figure 1. Agricultural Diversity, 1860



of the sample), about a third had a share of population in manufacturing above the median value in 1900.

Figures 2a and 2b show the spatial distribution of the share of population in the industrial sector in 1900 and personal income per capita in 2000. Not surprisingly, 1900 levels of industrialization are higher in the North than in the South. Here again, beyond regional disparities, there is significant variation within states. Figure 3b displays some similar patterns, with its most salient feature being the concentration of high income levels in the Northeast megalopolis.

Figure 2a.
Share of Population in Manufacturing, 1900

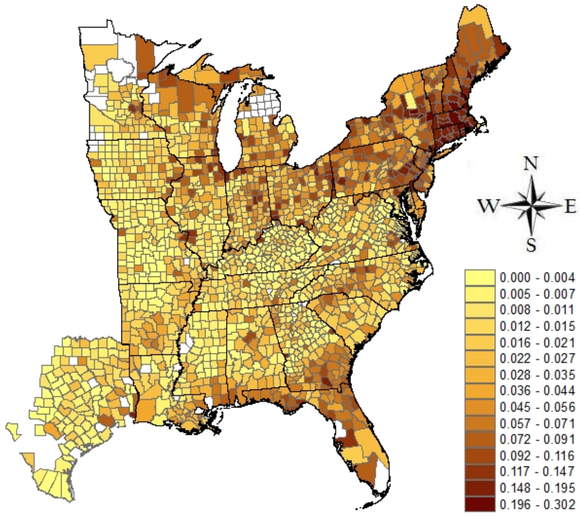
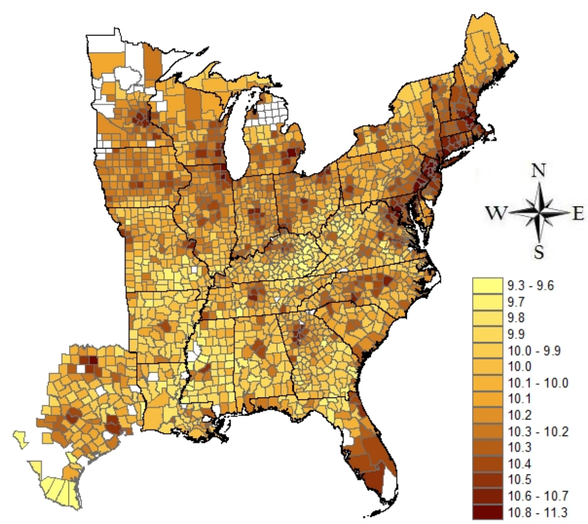


Figure 2b.
Ln Income per capita, 2000



3.2 Estimating Equation and OLS Results

This section presents the basic specification and OLS results. The estimating equation is

$$y_c = \beta_0 + \beta_1 \text{Agri.Diversity}_{c,1860} + \beta_2^{'} \mathbf{X}_c + \beta_3^{'} \mathbf{M}_{c,1860} + \delta_s + \varepsilon_c \ . \tag{1}$$

where y_c is a development outcome (such as income per capita or the share of population in manufacturing, at different points in time), $\mathbf{X}_c$ is a vector of time-invariant controls, and $\mathbf{M}_{c,1860}$ is a vector of initial conditions (i.e. variables measured at the beginning of the period under consideration), δ_s is a state fixed effect, and ε_c is an error term.

The vector of time-invariant controls, $\mathbf{X}_c$, comprises a rich set of variables. First, I control for a host of ecological variables. I include a measure of land suitability for cultivation (Ramankutty et al., 2002) as well as productivity measures based on product-specific potential yields (the max and average of attainable yields for the five major products).[5] Including these land productivity controls is crucial to avoid confounding the effects of agricultural diversity with the effects of agricultural resource abundance. To get unbiased estimates of the effects of diversification, it is essential that the estimates do not pick up the effects of other variables that may be significantly correlated with diversity and have an independent effect on the outcome variable. With this in mind, I also control for mean annual temperature, terrain elevation, latitude and longitude. The results are robust to controlling for flexible polynomials of all these ecological variables.

In addition, the set of time-invariant controls includes distances to major urban centers (New York, Chicago, Boston, Philadelphia and New Orleans) and waterways (the Coastline or the Great Lakes) measured in logs. These distances, which might be correlated with initial agricultural diversity in this sample, could affect the market access of industrial production and the inflow of new ideas, and thus including them as controls is important to avoid omitted variable bias.

Among the set of initial conditions, $\mathbf{M}_{c,1860}$, I include crop-specific controls. Since the Herfindahl index is a non-linear function of individual shares, and some particular agricultural products (wheat, corn, hay, cotton, animals slaughtered) represent large shares of agricultural output, these shares may be strongly correlated with diversfication at the county-level; thus, the estimated coefficient for diversity could pick up the positive or negative effect of being specialized in one of those particular products. To address that identification issue, I include dummies for those 5 major agricultural products that take a value of 1 when the

[5] These data are explained in detail in section 4.1 and Appendix A. To make yields for different products comparable, each product-specific attainable yield is normalized by the max attained in the sample before computing the max and average.

product has the largest share in a county's agricultural production.[6] I also control for the extent of plantation crops (i.e., the combined share of cotton, tobacco, sugarcane, and rice), which is emphasized by Engerman and Sokoloff (1997, 2002) to explain the US North-South divide. Although this divide does not affect the estimated coefficient of diversity when state fixed effects are included, the prevalance of plantations crops could remain relevant to explain cross-county within state variation in development outcomes.

Within the set of initial conditions I also consider an array of socio-economic controls, including the urbanization rate, population size (in logs), farm output (in logs), the shares of people below 15 and above 65 years of age, the share of slaves in the population, access to railroads, and a measure of "market potential," all for 1860. Following the classic definition of Harris (1954), market potential in county c is given by $\text{Market}_c = \sum_{k \neq c} d_{c,k}^{-1} N_k$, where k is the index spanning neighboring counties, $d_{c,k}$ is the distance between county c and county k, and N_k is the population of county k (here, in 1860).[7] Since trade theory posits that access to market induces specialization and also enhances economic performance, including market potential as a control may avoid a potentially sizeable (negative) bias in the estimated effect of diversity.

All the controls included in $\mathbf{M}_{c,1860}$ are predetermined with respect to the outcome variable, but they are potentially endogenous and thus their inclusion may introduce bias in the estimates. Because they are not predetermined with respect to the regressor of interest, they may be "bad controls," as explained by Angrist and Pischke (2008). If any of these variables reflect mechanisms through which diversification affects productivity, including them as controls would mask the true effect. For these reason, my preferred specification does not include these "initial conditions" as controls. However, if there is a correlation between agricultural diversity and these variables that does not reflect casuality from the former to the latter, then including these as controls would be necessary to avoid omitted variable bias. Thus, even if it is hard to argue that they are exogenous, it may be considered reassuring that the results remain robust when controlling for those variables.

Table 2 shows OLS estimates of the coefficient on agricultural diversity in 1860 when the set of controls is expanded sequentially in regressions with income per capita in 2000 (Panel

[6]These dummy variables are meant to capture the idea of dominance reflected in terms such as "cotton counties" or "wheat counties." The results are not qualitatively affected if I consider alternative crop-specific control variables (see Appendix B).

[7]Donaldson and Hornbeck (2012) show that Harris' *ad hoc* measure is similar to a first-order approximation to market access derived from an Eaton-Kortum general equilibrium trade model, with the diferrence that neighboring populations are not weighted by inverse distances but instead by the inverse of trade costs elevated to the trade elasticity, for which they use a baseline value of 3.8. Measuring market potential as $\text{Market}_c = \sum_{k \neq c} d_{c,k}^{-3.8} N_k$ does not qualitatively affect the results presented in the paper.

A) and the share of population in manufacturing in 1900 (Panel B) as outcome variables. The OLS estimates of the coefficient on agricultural diversification are positive and significant in all specifications and for both development outcomes.[8]

Table 2. Agricultural Diversity and Development: OLS Results

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. *Dependent variable: Ln Income per capita 2000*						
Agri.Diversity$_{1860}$	0.547***	0.241**	0.290***	0.333***	0.310***	0.287***
	(0.0781)	(0.105)	(0.0869)	(0.0564)	(0.0612)	(0.0609)
R^2	0.102	0.297	0.355	0.410	0.420	0.492
Panel B. *Dependent variable: Share of Population in Manufacturing 1900*						
Agri.Diversity$_{1860}$	0.0985***	0.0358**	0.0408***	0.0423***	0.0246***	0.0289**
	(0.0160)	(0.0102)	(0.0099)	(0.0107)	(0.0106)	(0.0113)
R^2	0.087	0.439	0.460	0.480	0.491	0.618
State FE	N	Y	Y	Y	Y	Y
Ecological controls	N	N	Y	Y	Y	Y
Distances to water and cities	N	N	N	Y	Y	Y
Crop-specific controls	N	N	N	N	Y	Y
Socio-economic controls	N	N	N	N	N	Y
Observations	1,821	1,821	1,821	1,821	1,821	1,821

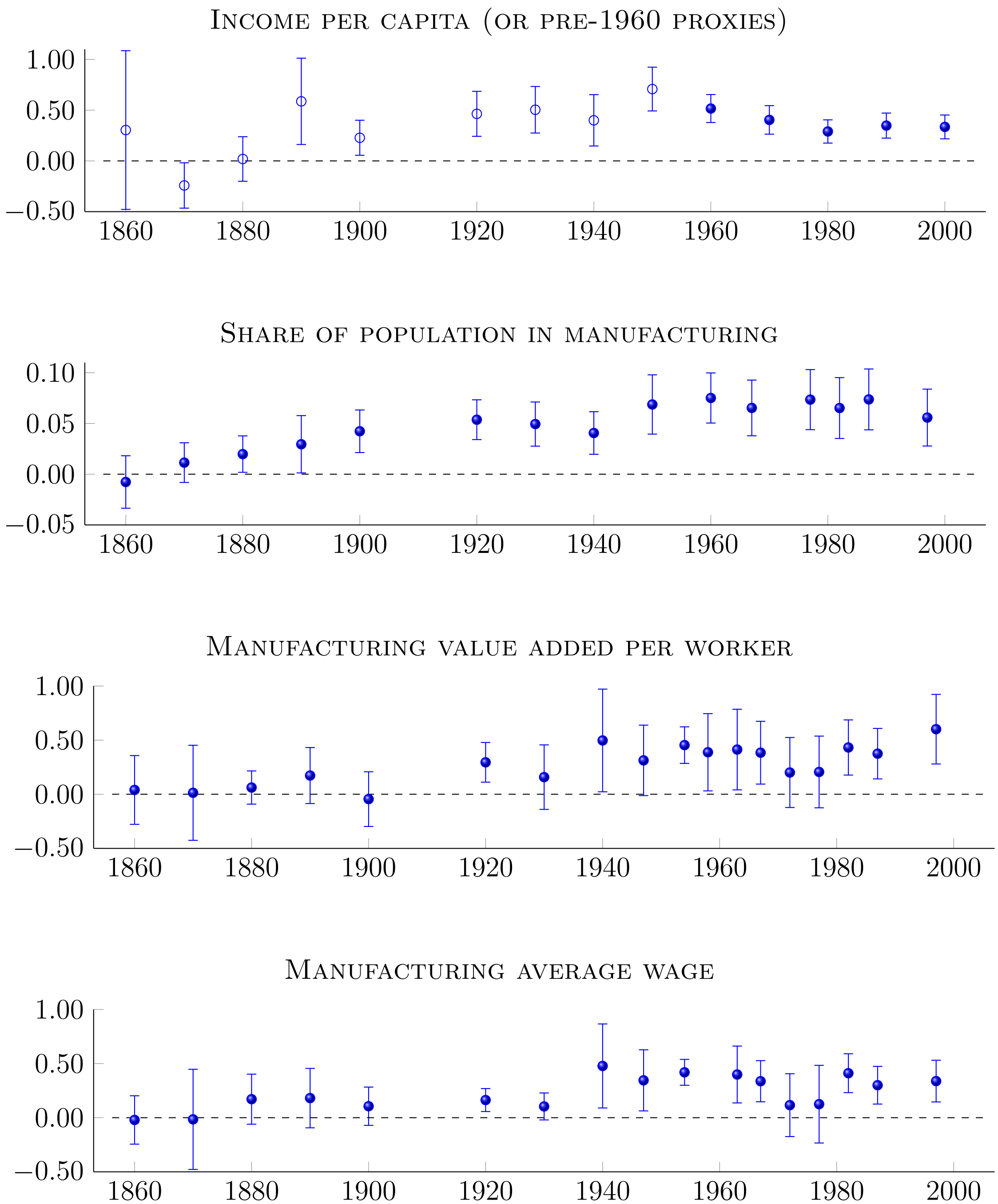
Notes: See Appendix A for variable definitions and sources. Robust standard errors clustered at the state level are reported in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

The table reports robust standard errors clustered at the state level. Conley (1999) standard errors adjusted for spatial dependence with cuttoffs of 50, 100 and 150 miles, are lower than standard errors clustered at the state level for all specifications (the table only reports the latter; a table including the former are available upon request).

Figure 3 shows estimates of the coefficient on Agri.Diversity$_{1860}$ for different outcome variables at different times (with the corresponding 95% confidence intervals) for my preferred specification. The results show a robust association between early agricultural diversity and recent income per capita levels. The share of population employed in the manufacturing sector, which can be interpreted as a measure of the extent of the industrialization process, shows correlations with initial agricultural diversity that increase over time and are significant from 1900 onwards.

[8] The results remain qualitatively the same when considering alternative measures of agricultural diversification (see Appendix C). The results are also robust to controlling for the (logarithm of) initial manufacturing labor productivity; this variable does not appear to be significant, and its inclusion barely changes the estimate for the coefficient of interest. In what follows this variable will not be taken into account, since it is known that lagged dependent variables bias the estimations (see, e.g., Bond, 2002).

Figure 3. Agricultural Diversity and Development Outcomes



Notes: The graphs display the estimated coefficients on agricultural diversity from regressions for different outcomes variables, controlling for state fixed effects, ecological controls and distances to water and cities. Intervals reflect 95% confidence levels. For income per capita and share of population in manufacturing, all regressions have 1,821 observations. For manufacturing productivity and wages, sample size fluctuates between 1,616 and 1,821; the estimates of coefficients for agricultural diversification 1860 are similar if regressions are performed with the largest possible stable sample for outcomes at different points in time. Pre-1960 income per capita are not available; as proxies, I use the sum of manufacturing and agricultural output over population for 1860-1940, and median family income over average family size for 1950.

4 Instrumental Variable Strategy and Results

The estimations presented in the previous section uncover suggestive correlations, but cannot be taken as evidence of a causal relationship. The positive correlation between agricultural diversity and development could be driven by omitted variables that induced higher diversification in 1860 and also improved subsequent economic performance. For example, diversity might reflect high propensity to adopt new ideas and/or higher human capital, which would also boost industrial development.[9]

On the other hand, if there are omitted variables that are negatively correlated with diversity and positively associated with subsequent economic perfomance, the OLS estimates would be negatively biased. For instance, diversity might partly reflect a higher level of risk aversion, which could in turn hamper productivity growth in the nascent manufacturing sector if this activity was perceived as highly risky. Higher diversification could also reflect the predominance of traditional agriculture (whereby farmers grow most of what they need for their own subsistence), which may in turn be associated with poor economic outcomes. Market access would also introduce a negative bias if not adequately captured by the controls: the extent of potential gains from trade would induce both specialization and growth. In addition, measurement error in agricultural production may introduce attenuation bias in the OLS estimates.

With the aim of identifying the causal effects of agricultural diversity on economic development, this section introduces an instrumental variable strategy that relies on exogenous variation in agricultural diversity generated by climatic features.

4.1 Agricultural Productivity Data and IV Construction

The proposed identification strategy exploits variation in agricultural diversity created by dispersion in product-specific productivities determined by climatic features. The FAO's Global Agro-Ecological Zones project (GAEZ) v3.0 provides measures of potential productivity for different crops based on climatic data and crop-specific characteristics. World

[9]For example, farmers' education could drive both the adoption of crop rotation schemes and subsequent growth (agricultural production data was collected for one-year periods, so diversity reflects to some extent the prevalence of crop rotation). Another possibility implying the same type of bias would be that diversification resulted from a more diversified local demand for agricultural goods due to higher purchasing power (not fully captured by the control variables), which would in turn be correlated with long-run development. A positive correlation between diversity in the demand for agricultural products and income levels could arise if some goods (e.g. meat, cheese, fruits) are superior. However, the opposite implications about the correlation of diversification with income (and thus with subsequent development) could be drawn from the fact that some agricultural staples are inferior goods.

maps with fine spatial resolution display crop-specific maximum attainable yields, measured in tons per hectare per year.[10] I also use a measure of grazing suitability from Erb et al. (2007). Appendix A describes all these data in detail.

Figure 4 displays the county-level average values of land suitability and selected crop-specific productivities (corn, wheat and cotton). Interestingly, the region in the Midwest commonly known as the Corn Belt seems to correspond more closely to the region where wheat productivity is highest, while corn productivity is high in the Corn Belt but highest in a southeastern region overlapping with the Cotton Belt. As these broad regional patterns, we need to think in terms of *relative* productivities.

The key of the identification strategy is that agricultural diversity is influenced by the dispersion of potential productivities for different crops. Intuitively, a county that has similar levels of productivity for many different crops is likely to be more diversified than a county with productivity for one crop much higher than productivities for all other crops. To construct an instrumental variable based on crop-specific productivities from GAEZ, I estimate a fractional multinomial logit (FML) for the shares of specific agricultural products in total agricultural output at the county level. The FML framework (due to Sivakumar and Bhat, 2002) generalizes the fractional logit model (Papke and Wooldridge, 1996) to an arbitrary number of choices, and can be readily applied in the context under consideration, as explained below (see Mullahy, 2011; Ramalho et al., 2011, for recent discussions).

The FML model estimates by quasi-maximum-likelihood a system of equations in which the outcome variables are the shares of each product in total agricultural output in county c (that is, θ_{ic} for $i = 1, 2, ..., 36$) as functions of the vector of product-specific productivities $\mathbf{A}_c$.[11] The functional form considered is

$$\hat{\theta}_{ic} = E[\theta_{ic}|\mathbf{A}_c] = \frac{e^{\beta_i' \mathbf{A}_c}}{1 + \sum_{j=1}^{I-1} e^{\beta_j' \mathbf{A}_c}} \quad . \tag{2}$$

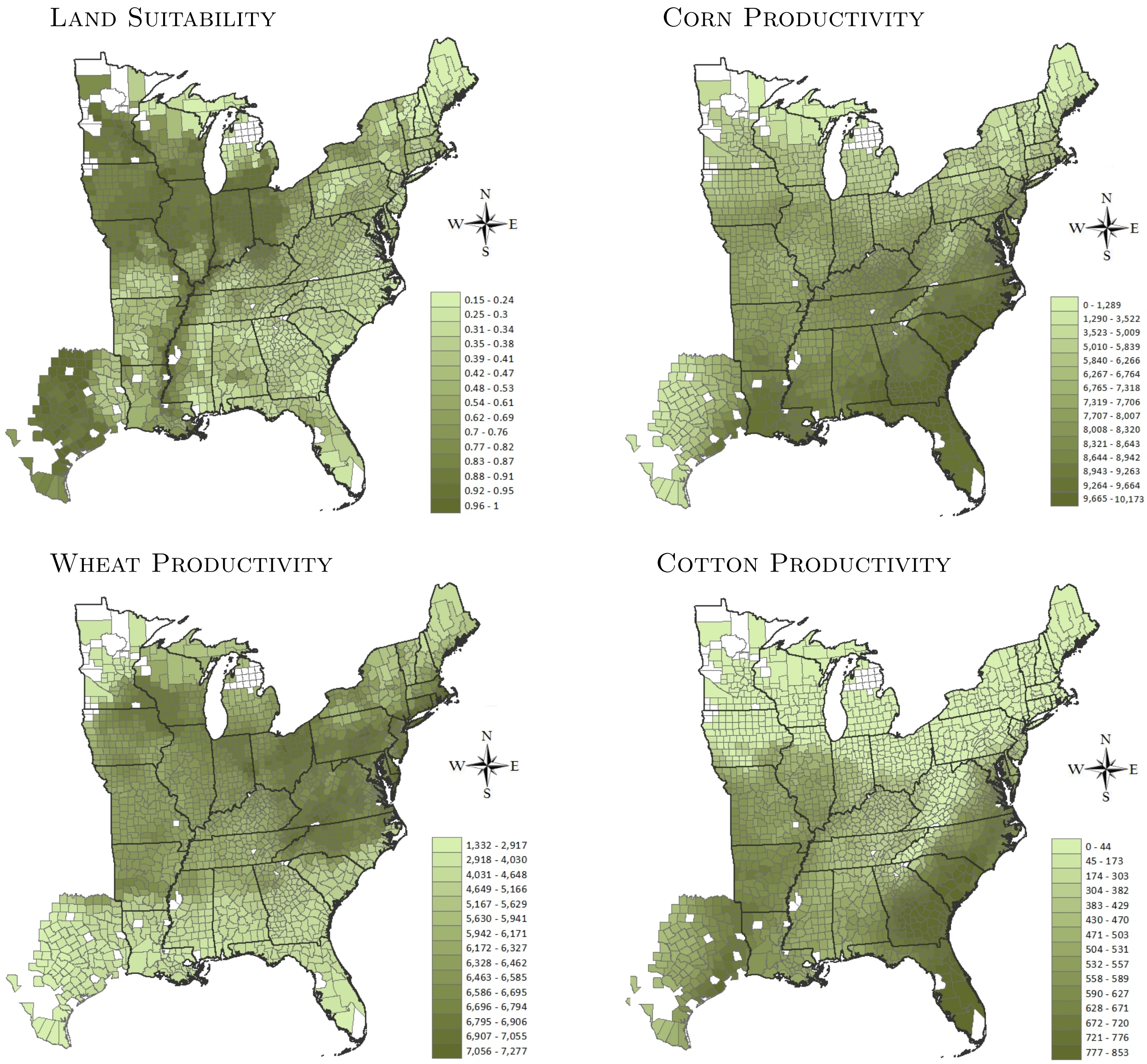
By construction, $\sum_{i=1}^{I} \hat{\theta}_{ic} = 1$, i.e. the predicted shares for each county add up to 1.

This econometric framework can be motivated by a simple optimal crop choice model. Recasting the conditional logit framework of choice behavior due to McFadden (1974) in

[10]Crop yields are constructed for alternative levels of inputs/technology (low, medium, high) and irrigation conditions – I consider the medium level of inputs/technology and rain-fed conditions in my baseline estimations, as these correspond most closely to the context under consideration.

[11]In the empirical estimation, the vector of productivities includes 22 relevant crop-specific productivities available from FAO (barley, buckwheat, cotton, maize, oats, pasture grasses, pasture legumes, alfalfa, potato, sweet potato, rye, cane sugar, tobacco, rice, wheat, tomato, carrot, cabagge, onion, pulses, sorghum, flax), the measure of grazing suitability, and the general measure of land suitability for agriculture from Ramankutty et al. (2002), to help to predict the shares of the products for which there is no productivity data available.

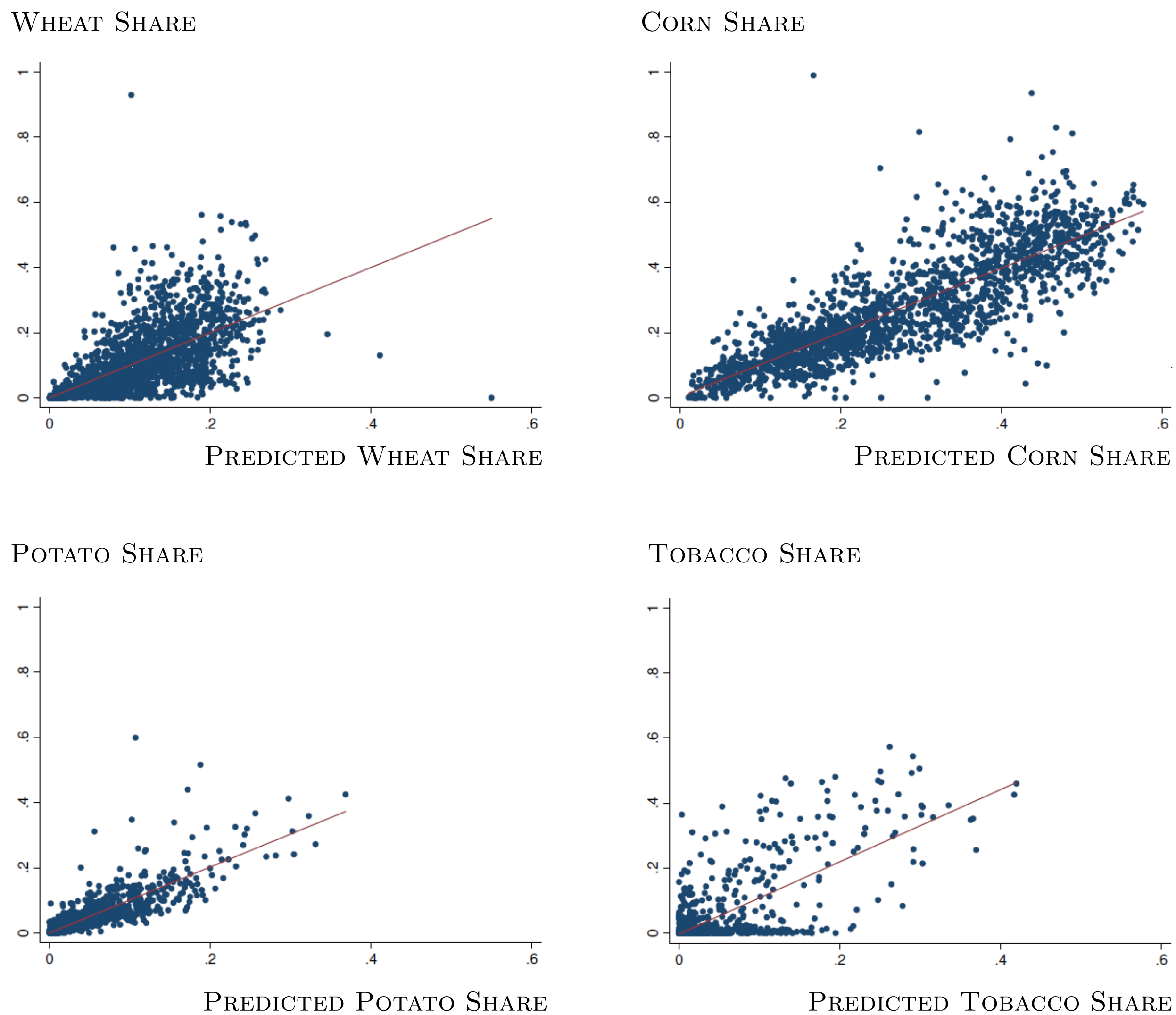
Figure 4. Land Suitability and Selected Crop-specific Productivities



terms of profit maximization rather than utility maximization, assume that profits obtained when choosing crop i for a unit of farm resources j are $\pi_{ij} = \beta_i' \mathbf{A}_j + \mu_{ij}$. The relative magnitudes of the β_i's reflect the price and cost differentials among agricultural products, as well as any other factors that affect profits for different crops; farmers are assumed to be price-takers. If the error term μ_{ij} is assumed to be *iid* with type I extreme value distribution, then choice i is optimal (i.e. $\pi_{ij} \geq \pi_{i'j}$ for all i') with probability $\frac{e^{\beta_i' \mathbf{A}_j}}{1+\sum_{j=1}^{I-1} e^{\beta_j' \mathbf{A}_j}}$.

Figure 5 plots actual against predicted shares for selected agricultural products. The estimation of the multinomial fractional logit model for US counties in 1860 produces a reasonably good fit for most agricultural products. For major crops, like wheat, corn and cotton, the fit is remarkably good. The fit is not as good for marginal crops, like rice or cane sugar, for which most observations lie close to the origin, with very low predicted shares and zero actual shares. But the linear fit shows a positive slope in all 36 agricultural products.

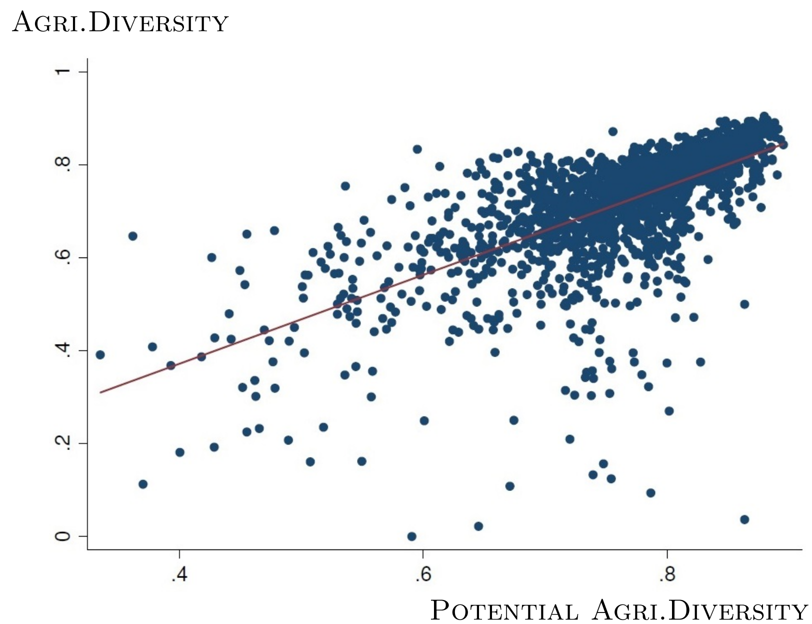
Figure 5. Actual and Predicted Shares of Selected Crops



Once the coefficients of the fractional multinomial logit have been estimated and used to calculate predicted shares for each agricultural product, I can calculate a measure of potential agricultural diversity based on those estimates and the crop-specific productivities for each county. This measure is obtained by simply taking the formula for diversity and substituting predicted shares for actual shares, i.e. Potential Agri.Diversity$_c = 1 - \sum_i \hat{\theta}_{ic}^2$. Insofar as the predicted shares calculated earlier are good predictors of the actual shares, the measure of potential diversity can be a good predictor of actual diversity. The scatterplot of the latter variable against the former in Figure 6 seems to indicate high predictive power in this sample. Figure 7 shows the spatial distribution of potential diversity.

A possible concern regarding the exclusion restriction is that the measures of land productivity could capture actual agricultural production conditions rather than exogenous geographic characteristics. However, these measures are calculated from climate data and expert knowledge of production processes for different crops, and not from statistical analysis of actual production patterns around the world.

Figure 6. Actual and Potential Agricultural Diversity



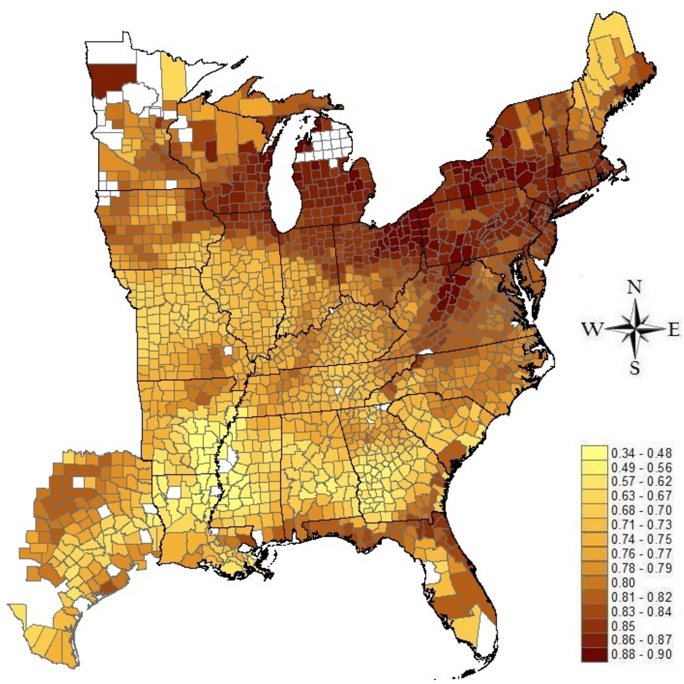
4.2 IV Estimates

I estimate the effect of agricultural diversity using potential agricultural diversity (contructed as explained above) as an IV. Table 3 reports the IV estimates of the effects of diversity on development outcomes for the three specifications corresponding to columns (1), (4) and (6) of Table 2, respectively including: no controls; state fixed effects, land productivity controls, and distances to water and cities; the previous controls plus crop-specific controls and socio-economic controls. In each case, the corresponding OLS estimates from Table 2 are reproduced to facilitate comparison.[12]

[12] A sufficient condition for the standard errors to be correct when using the generated IV is that the expectation of the error term in the estimating equation conditional on the measures of potential productivity used in the IV construction is equal to zero, $E(\varepsilon_c|\mathbf{A}_c)=0$ (see Wooldridge, 2010). Insofar as the estimating equation adequately controls for measures of overall land productivity and climatic variables that may affect

Panel A shows the effects on income per capita in 2000, and Panel B of Table 3 shows results with the share of population in manufacturing in 1900 as the outcome variable. Panel C displays the results of the first stage. The IV estimates indicate positive and significant effects of agricultural diversity in 1860 on the size of the manufacturing sector in 1900 and on income per capita in 2000. IV estimates from specification 2 indicate that an increase of one standard deviation in agricultural diversity in 1860 (approximately 0.125 in the index) led to an increase of 0.65 percentage points in the share of population in manufacturing in 1900 and a 5% gain in income per capita in 2000.

Figure 7. Potential Agricultural Diversity



Results from the first stage displayed in Panel C show that the IV has very high predictive power in all specifications, though the magnitude of the estimated coefficient goes down when additional controls are included. In all cases, the F-statistics for the significance of the IV in the first stage are large, and the p-values from the rank test for weak instruments developed by Kleibergen and Paap (2006) indicate rejection of the null hypothesis of weak instruments.

The IV estimates are larger in magnitude than the OLS estimates. This difference may be due to measurement error in agricultural diversity – the IV estimates could be correcting for

development outcomes, the sufficient condition is satisfied. In any case, bootstrapped standard errors are similar to the ones reported in this section and the significance levels of the estimated coefficients remain unchanged (results are available on request).

attenuation bias generated by measurement error. A negative bias in the OLS estimates could also be explained by omitted variables that are negatively correlated with diversification and positively associated with subsequent economic perfomance, as discussed above. In any case, for specifications 2 and 3, a Hausman test cannot reject the null hypothesis that the OLS estimates are consistent.

Table 3. Agricultural Diversity and Development: IV Estimates

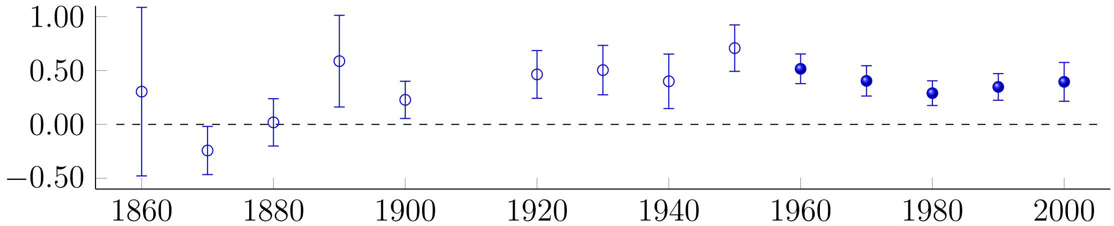
	Specification 1		Specification 2		Specification 3	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Second Stage. *Dependent variable: Ln Personal Income per capita 2000*						
$\text{Agri.Diversity}_{1860}$	0.547***	0.866***	0.333***	0.395***	0.287***	0.417**
	(0.0781)	(0.117)	(0.0564)	(0.0918)	(0.0609)	(0.197)
R^2	0.102	0.067	0.410	0.409	0.492	0.489
Panel B. Second Stage. *Dependent variable: Share of Population in Manufacturing 1900*						
$\text{Agri.Diversity}_{1860}$	0.0985***	0.161***	0.0423***	0.0519**	0.0289**	0.110**
	(0.0160)	(0.0350)	(0.0107)	(0.0201)	(0.0113)	(0.0459)
R^2	0.087	0.052	0.480	0.082	0.618	0.292
Panel C. First Stage. *Dependent variable: Agricultural Diversity 1860*						
Potential Agri.Diversity		0.956***		0.703***		0.489***
		(0.0858)		(0.0892)		(0.108)
R^2		0.436		0.555		0.624
F-stat		124.16		62.12		20.54
Kleibergen-Paap p-value		0.000		0.000		0.000
State FE	N	N	Y	Y	Y	Y
Ecological controls	N	N	Y	Y	Y	Y
Distances to water and cities	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: See Appendix A for variable definitions and sources. Robust standard errors clustered at the state level are reported in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

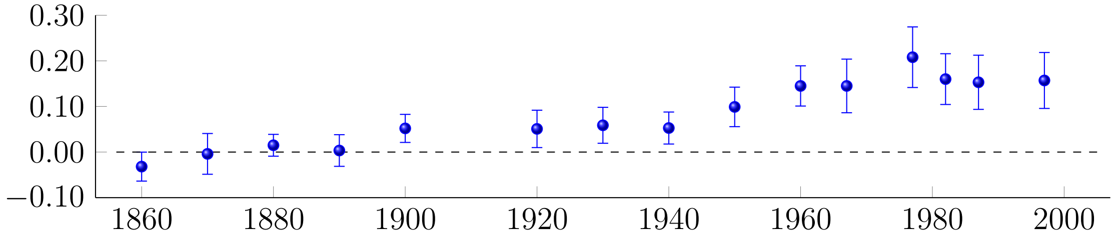
Figure 8 shows estimated effects of agricultural diversity in 1860 on income per capita and the extent of the industrialization at different times (with the corresponding 95% confidence intervals) for my preferred specification. The results indicate that early agricultural diversity shaped the process of industrialization and had a positive impact on development outcomes that emerged around the turn of the century.

Figure 8. Effects of Agricultural Diversity on Development Outcomes

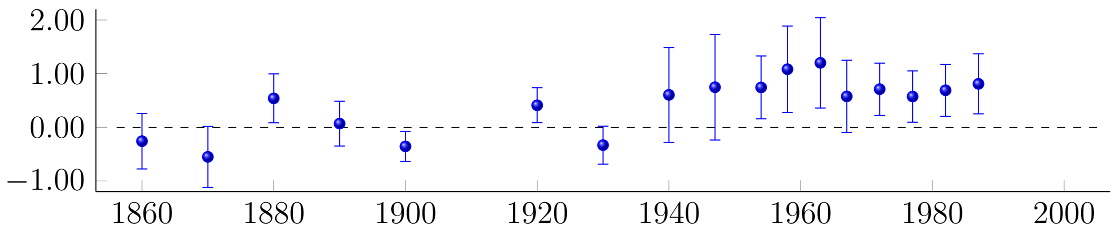
Income per capita (or pre-1960 proxies)



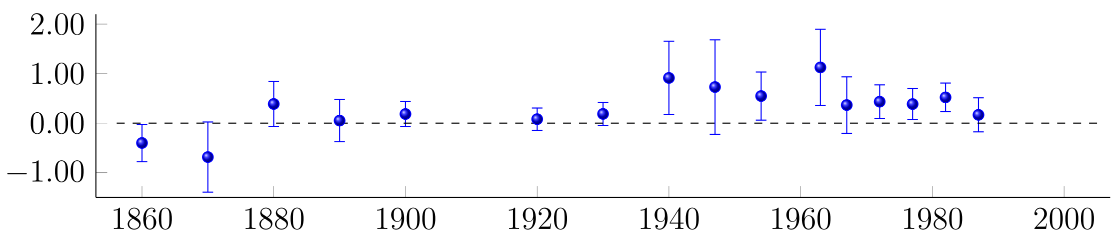
Share of population in manufacturing



Manufacturing value added per worker



Manufacturing average wage



Notes: The graphs display the estimated coefficients on agricultural diversity from regressions for different outcomes variables, controlling for state fixed effects, ecological controls and distances to water and cities. Intervals reflect 95% confidence levels. For income per capita and share of population in manufacturing, all regressions have 1,821 observations. For manufacturing productivity and wages, sample size fluctuates between 1,616 and 1,821; the estimates of coefficients for agricultural diversification 1860 are similar if regressions are performed with the largest possible stable sample for outcomes at different points in time. Pre-1960 income per capita are not available; as proxies, I use the sum of manufacturing and agricultural output over population for 1860-1940, and median family income over average family size for 1950

5 Mechanisms: Diversity, Skills, and Technical Progress in the Second Industrial Revolution

Having established the significant positive effects of agricultural diversity on long-run development, I proceed to examine the channels that may explain these effects. Various mechanisms proposed by growth theory and urban economics (discussed in section 2) could generate the observed relationships. This section suggests that the impact of early agricultural diversity on the process of industrialization operated through increased variety of industrial products and skills, formation of novel productive capabilities, and technological progress. Although these channels are distinct, they are tightly connected and largely complementary (as emphasized by the model proposed in section 6). The analysis below provides evidence regarding their plausibility without attempting to disentangle quantitatively the contribution of each channel.

My approach consists in estimating the impact of early agricultural diversity on intermediate variables that capture those channels in order to estabish their plausibility. Following the results of previous sections indicating that the impact of early agricultural diversity emerged over the course of the Second Industrial Revolution, I focus on outcomes at the culmination of that historical period (Appendix D shows how the effects emerged over the period).

Other channels that may explain the effects of agricultural diversity on development are examined in Section 7. Overall, the evidence does not support their relevance. Of particular note is the absence of evidence that the impact of agricultural diversity operated through agricultural productivity, which highlights the cross-sectoral nature of the effects of early agricultural diversity. Elucidating the workings of these cross-sectoral effects is the main purpose of this section.

While the channels considered here have been proposed by theories that refer to economy-wide diversity, they also shed light on the effects of *agricultural* diversity in the context studied here. These mechanisms could have been activated by diversity in agricultural activities, as suggested by some illustrative examples mentioned below. They could also have been activated by manufacturing diversification induced by initial agricultural diversity—as shown in section 5.1, diversity in agriculture can be the root of industrial diversity.

5.1 Diversity, from Agriculture to Manufacturing

Diversity in agricultural production may foster diversity in the manufacturing sector insofar as linkages between agricultural and non-agricultural products influence local patterns of production. As Hirschman (1981) put it, "development is essentially the record of how one thing leads to another, and the linkages are that record." Thus, producing a wider range of (agricultural) things at early stages of development could lead to a more diverse set of (industrial) things later on.

Page and Walker (1991) document a number of linkages between different agricultural products and industrial sectors in the late nineteenth century US, with a focus on the "agro-industrial revolution" in the American Midwest. Flour milling, the nation's largest industrial sector in production value between 1850 and 1880, was the main source of demand for wheat. Rye, barley, and corn were used by distilling industries to make spirits. Breweries made beer using hops and barley, and sometimes other grains as well. Cattle raisers were suppliers of the rising meatpacking industry and leather industries.

In turn, agro-processing industries—which at those times were technologically progressive and accounted for a large share of GDP—had multiple forward and backward linkages. Grain processing supplied bakeries, confectionery establishments, and other food industries. Meatpacking establishments produced not only meat products and leather, but also lard, candles, glue and fertilizer. Agro-processing industries also induced some paradigmatic innovations of the nineteenth century, such as the grain elevator and railroads' refrigerator cars (Cronon, 2009).

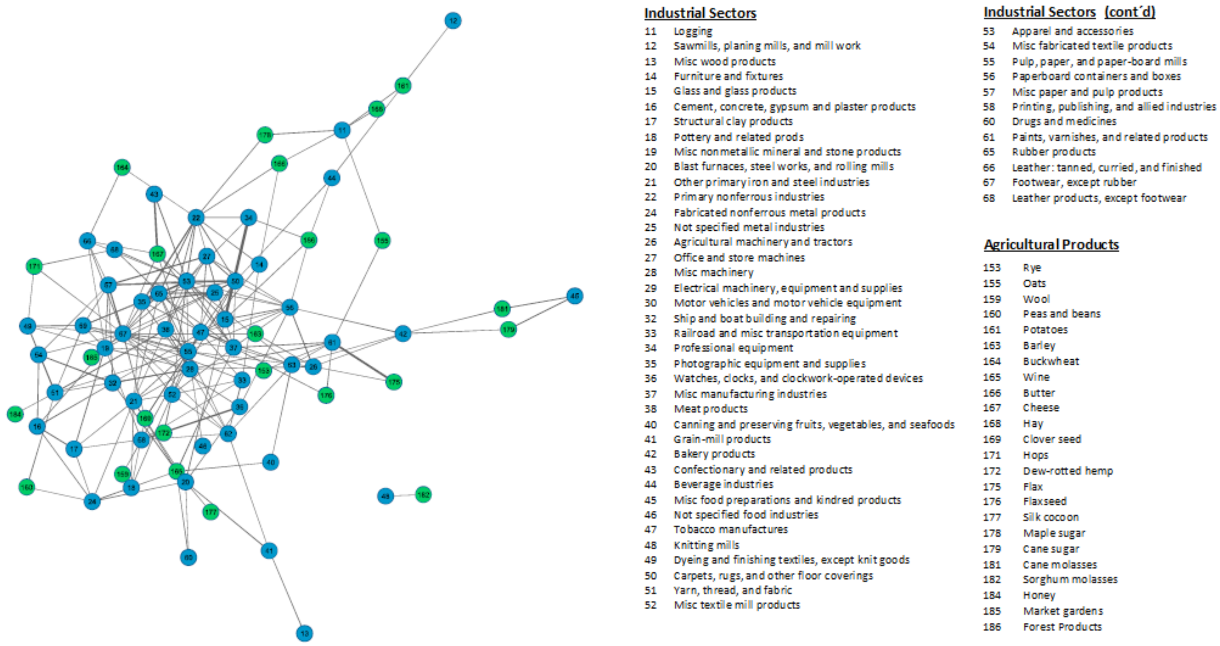
Linkages between different products can be generated by input-output relationships as well as by common labor skills or knowledge spillovers, as emphasized by Ellison et al. (2010) in their study of industry co-agglomeration patterns. Going back to Marshall (1895), the costs of moving goods, people and ideas can all be reduced by agglomeration, thus providing different sources of industry co-location. Looking at plant-level data from the 1987 US Census of Manufactures (at the state, PMSA, and county levels), Ellison et al. (2010) find that input-output dependencies, correlations in labor skills, and technology flows are all important in explaining industry co-agglomeration patterns.

For illustration purposes, Figure 9 shows the network structure of industrial and agricultural production. The network graph displays pairwise positive and significant correlations between sectoral employment shares across counties in the sample in 1860 (see notes for details). The links in this network thus capture any type of linkage (as well as, possibly, sample noise); Appendix E provides a network representation of the structure of production based exclusively on input-output linkages, with the same broad implications. The figure advances two main insights: (1) the network displays a clustered structure and heterogeneity in nodes' connectivity;[13] (2) agricultural products are scattered throughout the network.

[13]Network heterogeneity –associated with the presence of hubs–, measured by the coefficient of variation of nodes' connectivity (i.e., nodes' number of neighbors), is 0.78; the network clustering coefficient, measured

The implication is that various agricultural products provided different "entry points" into the industrial sectoral network of production.

Figure 9. Agricultural Products in the Production Network



Notes: The network is defined by the collection of (statistically significant at the 5% confidence level) pairwise correlations between sectoral employment shares across counties in the sample in 1860 (represented by the links between nodes). The visual arrangement relies on a spring-embedded type of algorithm. I consider pairwise correlations between agricultural products and industrial sectors as well as between two industrial sectors, but not those between two agricultural products. Only 50 (out of 59) industrial sectors and 26 (out of 36) agricultural products have at least one positive and significant correlation; the remaining sectors/products do not appear in this network graph. Employment shares for agricultural products are calculated by multiplying the employment share of agriculture in the county by the product's share in the county's agriculutural production value.

Consistent with the idea that early agricultural diversity can lead to higher economy-wide diversity due to the various linkages of agricultural products, Panel A of Table 4 shows positive and significant impacts on a measure of diversity across manufacturing sectors in 1920.[14] I report OLS and IV estimates for the same three specifications used before.

by the average *local* clustering coefficients (actual over potential connections among the neighbors of a node), is 0.184.

[14]Like other outcome variables considered in this section, the index sectoral diversification (see details in Table 4's notes) is computed with employment data from the 1-in-100 sample of the 1920 Census, which reports employment microdata with at least one manufacturing worker for 1,676 counties; the remaining 145 counties in the sample have missing data for these indexes. The main results presented in paper so far (i.e. those reported in Tables 2 and 3) are qualitative the same if the estimating equations are run for the reduced sample of 1,676 counties with dissaggregated manufacturing employment data.

Table 4. From Agricultural Diversity to Industrial Diversity

	Specification 1		Specification 2		Specification 3	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. *Dependent variable: Industrial Sectoral Diversification 1920*						
Agri.Diversity$_{1860}$	0.615***	0.905***	0.268***	0.394**	0.188*	0.481*
	(0.111)	(0.205)	(0.0711)	(0.188)	(0.0925)	(0.286)
R^2	0.067	0.052	0.266	0.265	0.320	0.314
Panel B. *Dependent variable: Industrial Skills Diversification, 1920*						
Agri.Diversity$_{1860}$	0.378***	0.651***	0.233***	0.378**	0.175**	0.483**
	(0.0847)	(0.175)	(0.0867)	(0.171)	(0.0768)	(0.220)
R^2	0.034	0.016	0.211	0.208	0.269	0.260
State FE	N	N	Y	Y	Y	Y
Ecological controls	N	N	Y	Y	Y	Y
Distances to water and cities	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	1,676	1,676	1,676	1,676	1,676	1,676

Notes: Industrial sectoral diversification is measured as 1 minus the Herfindahl index of manufacturing employment shares across 59 different sectors in total manufacturing employment. Industrial skill diversity is calculated as 1 minus the Herfindahl index of manufacturing employment shares in each of 75 different white collar and blue collar occupations and a 76th category for all unskilled workers. See Appendix A for other variable definitions and sources. Robust standard errors clustered at the state level are reported in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

A broader array of productive activities could yield efficiency gains under imperfect substitutability between inputs, as in endogenous growth models with expanding varieties or New Economic Geography models. For industrial products requiring a variety of raw materials, agricultural diversity could have direct positive effects on productivity. Even if no single industrial product required more than one agricultural input, shortages of particular agricultural products could affect particular industrial activities and have significant aggregate effects by propagating through inter-industry input-output linkages. Thus, the positive effects of agricultural diversity may have operated simply through increased variety of industrial inputs, insofar as agricultural diversity fostered industrial diversification (as shown on Panel A of Table 4).

The positive effects of diversity may also have to do with variety in skills. A broader array of agricultural products, each associated with different production processes, can induce the development of a wider range of specific skills, either directly required in agricultural production or in sectors connected through intersectoral input-output linkages. Consistent with this idea, Panel B of Table 4 shows positive and significant impacts on agricultural diversity in 1860 and on an index of skill diversity in the manufacturing sector in 1920. In turn, variety of skills could yield direct productivity gains in a similar way than input variety (e.g., a CES production function where specific skills are complements).

5.2 Novel Skills and Technology Flows

Beyond its possible direct impact on productivity, diversity may have triggered dynamic forces that favored the acquisition of new skills and boosted technology flows. Again, these mechanisms could have been activated more or less directly by agricultural diversity, or by manufacturing diversity induced by early agricultural diversification.

The dynamic effects of variety in skills are emphasized by Hausmann and Hidalgo (2011). Under the assumption that skills are complementary, higher levels of diversity may reflect a wider range of available skills (or more broadly, productive capabilities), entailing higher returns to acquiring new skills and thus implying not only a positive effect of diversity on the level of productivity but also on subsequent growth.

To assess the dynamic effect of diversity in the acquisition of new skills, I focus on the formation of skills that had a leading role in the Second Industrial Revolution. Using Census employment data, I identify a subset of occupations that were marginal or non-existent in 1860 but rose to prominence by 1920, such as electricians, tool makers, and auto mechanics.[15] Considering each of these 26 occupations as a specific skill, I compute a county-level measure of new skills formation as the count of these ocuppational categories that represented non-zero shares of the manufacuring labor force in 1920. Panel A of Table 5 reports estimates of the effects of initial agricultural diversity on the formation of new skills from Poisson regressions with the same sets of controls used in the baseline estimating equation. The results for all specifications, including IV estimates, are positive and significant.

Besides fostering the acquisition of new specific skills, diversity may favor general human capital formation. Education favors flexibility and adaptability to change, and facilitates the adoption of new technologies. A local economy using a wide set of production techniques may be characterized by high returns to education and thus favor human capital formation. Panel B of Table 5 reports regression results that assess the effect of agricultural diversity on literacy rates in 1920. Overall, the evidence is consistent with a positive and significant

[15]This subset of consists of 26 occupations for which the number of respondents in the Census microdata samples is either zero in 1860 or increased by over a factor of 50 from 1860 to 1920. Full details are provided in Appendix A.

effect of diversification on human capital formation in the long run.[16]

In addition to the effects on the acquisitions of new specific skills and general human capital, a more diversified economy may be more conducive to technological progress, as suggested by Jacobs (1969) and others. This effect can be explained by the role of cross-sector spillovers, recombination and complementarities in the dynamics of technology. Classic examples include windmills (which combine the principles of watermills and sails), the cotton spinning mule (which relied on the moving carriage from Hargreaves' spinning jenny and the rollers of Arkwright's water frame), and incandescent light bulbs (which reinvented candles on the basis of electricity). Well-known historical examples of cross-product spillovers include the origins of the bow in the bow drill, and more recently, baking soda, which in addition to its cooking uses has many applications in cleaning and personal hygiene products. An important case of complementarity from the Second Industrial Revolution were the correlative improvements in power generation and transmission networks.[17]

Some examples of complementarities and recombinant innovations from the American Second Industrial Revolution involve agro-processing industries and agricultural machinery producers, thus suggesting a direct link between agricultural diversity and technological dynamism. A salient illustration comes from the history of Ford Motors Company, which reveals that the concept of the production chain incorporated insights from flour mills, meat-packing establishments, breweries and canning factories (Hounshell, 1985). Other examples appear in the production of agricultural implements, which in the mid-nineteenth century was still characterized by small and medium establishments serving local markets, and was highly specialized by crop type (Pudup, 1987; Page and Walker, 1991). For example, corn, wheat, beans, and potatoes all used different types of mechanical planters. While improvements in tools and machines were often specific to one crop or group of crops, the enlargement of producers' know-how presumably yielded cross-product spillovers and higher potential for later recombinations. In addition, the agricultural machinery sector had technological complementarities with other industries; the development of the plow, for instance, relied heavily on advances in iron metallurgy (Pudup, 1987).

[16]Literacy rates are a limited measure of human capital formation. The results (not shown) are qualitatively the same considering as the outcome variable the average number of years education in 1940 (the first year for which this information is available in the Census data).

[17]The examples in this paragraph and some others are discussed by Rosenberg (1979), Desrochers (2001), and Akcigit et al. (2013).

Table 5. Effects of Agricultural Diversity on Innovation and Human Capital

	Specification 1		Specification 2		Specification 3	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. *Dependent variable: New Skills, 1920*						
	Poisson	IV-Poisson	Poisson	IV-Poisson	Poisson	IV-Poisson
Agri.Diversity$_{1860}$	4.808***	9.047***	2.098***	2.220*	1.327***	3.854*
	(0.246)	(0.923)	(0.313)	(1.321)	(0.333)	(2.303)
Panel B. *Dependent variable: Literacy rate of people 21+ years, 1920*						
	OLS	IV	OLS	IV	OLS	IV
Agri.Diversity$_{1860}$	0.346***	0.524***	0.171***	0.299***	0.0972***	0.145*
	(0.0739)	(0.109)	(0.0393)	(0.0933)	(0.0209)	(0.0838)
Panel C. *Dependent variable: Patents per 1,000 inhabitants, 1910-1920*						
	Tobit	IV-Tobit	Tobit	IV-Tobit	Tobit	IV-Tobit
Agri.Diversity$_{1860}$	0.864***	1.760***	0.303***	0.549**	0.156	1.043***
	(0.0783)	(0.124)	(0.0844)	(0.215)	(0.0974)	(0.400)
State FE	N	N	Y	Y	Y	Y
Ecological controls	N	N	Y	Y	Y	Y
Distances to water and cities	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: See Appendix A for variable definitions and sources. Robust standard errors clustered at the state level are reported in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

To assess the relevance of the technological progress channel, I study the effects of early agricultural diversity on a proxy for technological dynamism –patent counts by county per 1,000 inhabitants– between 1910 and 1920.[18] I interpret this variable as a proxy for local technological progress broadly defined, capturing not only innovation but also adoption and adaptation to local environments (most probrably, only a small fraction of patents led to actual shifts in the technology frontier, but counts of patents including unsuccessful ones can be interpreted as an indicator of technological dynamism). The estimates of the effects of early agricultural diversity from Tobit models, reported in Panel C of Table 5, appear as positive and significant across specifications (except for the Tobit estimation of specification 2, which yields a positive point estimate but with a large standard error).

[18]The patents data, which reports the location of each innovator, comes from Akcigit et al. (2013); I am very grateful to the authors for sharing their data. To calculate patents per 1,000 inhabitants, 1910-1920, I consider the location (latitude and longitude) given for each patent in the dataset and the boundaries of 1860 counties, and use 1910 population levels.

5.3 Testing Cross-County Cross-Industry Implications

The mechanisms emphasized above, which point to the role of complementarities, cross-fertilization, and recombination in the dynamics of skill formation and technology flows, suggest that the positive effects of diversity should be higher in skill-intensive and knowledge-intensive activities. In a study of industrial development in the US between 1970 and 1987, Henderson et al. (1995) find that young high-tech industries of the period (electronic components, medical equipment, and computers) were more likely to locate in cities with higher levels of industrial diversity. Beaudry and Schiffauerova (2009) discuss further evidence indicating that Jacobs externalities can be particularly important for the development of high-tech industries.

I study whether early agricultural diversity was conducive to the development of skill-intensive and knowledge-intensive industrial sectors following the approach of Rajan and Zingales (1998). I estimate cross-county cross-industry regressions where the outcome variable ($\vartheta_{s,c}$) is the percentage of manufacturing workers in county c employed in industrial sector s, and the key regressor is the interaction between early agricultural diversity at the county-level and an industry-level measure of complexity ($\text{Agri.Diversity}_{c,1860} \times \text{Complexity}_s$). The estimating equation is

$$\vartheta_{s,c} = \alpha_s + \alpha_c + \gamma \text{Agri.Diversity}_{c,1860} \times \text{Complexity}_s + \varepsilon_{s,c} \tag{3}$$

where α_s is an industry fixed effect and α_c is a county fixed effect. Skill-intensity is a measure of average educational levels of the industry's workers, while the measure of knowledge-intensity is the percentage of engineers and scientists in total industry employment in the US economy in 1950; the results are robust to considering the fraction of non-production workers in total industry employment, another standard measure of knowledge-intensity.

Table 6 shows regression OLS and IV estimates using the two different measures of sectoral complexity. The results indicate positive and significant effects of early agricultural diversity on the development of skill-intensive and knowledge-intensive industries.[19]

[19] Although estimates from probit and tobit models that explicitly take into account "corner solutions" could provide insight into the differential effects of early agricultural diversification on entry into skill-intensive and knowledge-intensive sectors, I refrain from adopting these specifications due to the issues presented by non-linear models under the presence of interaction terms (Greene, 2010).

Table 6. Differential Effects on Skill- and Knowledge-intensive Sectors

	Dependent variable: percentage of industrial workers in county c employed in sector s			
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Agri.Diversity$_{c,1860}$×Skill-Intensity$_s$	0.409***	0.711***		
	(0.0735)	(0.106)		
Agri.Diversity$_{c,1860}$×Knowledge-Intensity$_s$			0.467***	0.937***
			(0.010)	(0.131)
County fixed effects	Y	Y	Y	Y
Sector fixed effects	Y	Y	Y	Y
Observations	98,884	98,884	98,884	98,884
Counties	1,676	1,676	1,676	1,676
Industrial sectors	59	59	59	59
R^2	0.141	0.141	0.141	0.141

Notes: Observations are at the county-industry level. See Appendix A for definitions and sources of control variables and the measures of skill-intensity and knowledge-intensity. Robust standard errors are reported in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

6 A Model of Agricultural Diversity, Structural Change and Long-run Development

In this section I propose a simple multi-sector model of growth and structural change that explains the long-run effects of agricultural diversity. The framework highlights the interconnected roles of complementarities between sector-specific capabilities and cross-sectoral spillovers in the mechanics of structural change. These features of the model explain not only the positive effect of agricultural diversity on industrialization, but also its differential effect on relatively complex industrial sectors. The effects of agricultural diversity unfold over time as local economies go through critical junctures in which the number of capabilities originated in agriculture determines whether the process of structural change continues or ceases.

I consider a small local economy, open to trade and labor flows. Free trade implies perfectly elastic demands for all goods. This setup allows me to abstract from the demand side to focus only on the production side. Consumption decisions play no role in the model. In turn, under the simplest form of regional 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. The key assumption underlying the persistent nature of the effects of diversity is that productivity depends on local productive capabilities that are not mobile across locations.

6.1 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 price normalization), and can hire as much unskilled and skilled labor as they want at wage levels $\bar{w}_{u,t}$ and $\bar{w}_{s,t}$, which are taken as given in the local economy.

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 (unskilled) labor hired in plot p (to keep notation simpler, a time subindex t and a local economy subindex c are dropped whenever this does not give rise to confusion). To maximize profits ($\Pi_p = Y_p - \bar{w}_u L_p$), the owner of plot p hires $L_p^* = \left(\frac{\sigma}{\bar{w}_u}\right)^{\frac{1}{1-\sigma}} A_p x_p$.

Total agricultural employment in the local economy is $L_a^* = \left(\frac{\sigma}{\bar{w}_u}\right)^{\frac{1}{1-\sigma}} \bar{A}_a X$, 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 levels.

Agricultural output comprises a number of agricultural varieties, determined by exogenous climatic features. For simplicity, agricultural diversity is defined in the context of the model as the number of agricultural varieties and it is taken as a primitive rather than explicitly modeled as the outcome of optimal crop choice. In the analysis of comparative economic performance, land size and average land productivity will be kept constant across local economies, while disparities in agricultural diversity will be shown to drive disparities in long-run development.

Manufacturing Production

There are several industrial sectors (indexed by i), each of which may be active or not. For an active sector i, production is

$$Y_i = A_i^{1-\alpha} \left(L_{u,i}^{1-\gamma_i} L_{s,i}^{\gamma_i}\right)^{\alpha} \tag{4}$$

where A_i reflects sectoral productivity, $L_{u,i}$ and $L_{s,i}$ are, respectively, unskilled and skilled labor employed in sector i, and $\alpha \in (0,1)$. Decreasing returns to labor reflect limited entrepreneurial ability.

An active producer in sector i solves the optimization problem Max $\Pi_i = Y_i - \bar{w}_u L_{u,i} - \bar{w}_s L_{s,i}$, which determines the optimal quantities of unskilled and skilled labor (and thus total sectoral labor, L_i^*), as well as equilibrium output and profits:

$$L_{u,i}^* = \left[\tfrac{(1-\gamma_i)\alpha}{w_u}\left(\tfrac{\gamma_i}{1-\gamma_i}\tfrac{w_u}{w_s}\right)^{\gamma_i\alpha}\right]^{\frac{1}{1-\alpha}} A_i \ ; \quad L_{s,i}^* = \tfrac{\gamma_i}{1-\gamma_i}\tfrac{w_u}{w_s}L_{u,i}^* \ ;$$

$$L_i^* \equiv L_{u,i}^* + L_{s,i}^* = \left(1+\tfrac{\gamma_i}{1-\gamma_i}\tfrac{w_u}{w_s}\right)\left[\tfrac{(1-\gamma_i)\alpha}{w_u}\left(\tfrac{\gamma_i}{1-\gamma_i}\tfrac{w_u}{w_s}\right)^{\gamma_i\alpha}\right]^{\frac{1}{1-\alpha}} A_i \ ;$$

$$Y_i^* = \left[\tfrac{(1-\gamma_i)\alpha}{w_u}\left(\tfrac{\gamma_i}{1-\gamma_i}\tfrac{w_u}{w_s}\right)^{\gamma_i}\right]^{\frac{\alpha}{1-\alpha}} A_i \ ; \quad \Pi_i^* = (1-\alpha)Y_i^* \ .$$

There is heterogeneity across sectors in γ_i and $A_{i,t}$. Heterogeneity in γ_i implies variation in skill-intensity and average output per worker across sectors. Defining skill-intensity as the share of sector's workers that are skilled in equilibrium, we have that $h_i^* = \frac{L_{s,i}^*}{L_{u,i}^*+L_{s,i}^*} = \frac{w_s-w_u}{w_s} + \frac{1}{1-\gamma_i}\frac{w_u}{w_s}$, and thus $\frac{\partial h_i^*}{\partial \gamma_i} > 0$. Equilibrium output per worker is $y_i^* = Y_i^*/L_i^* = \frac{\frac{1}{\alpha}w_u w_s}{\gamma_i w_u + (1-\gamma_i)w_s}$, and thus $\frac{\partial y_i^*}{\partial \gamma_i} > 0$. The next subsection explains the source of heteregeneity in productivity across sectors.

6.2 Productivity and Local Capabilities

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 ($E_{i,c,t}$):

$$A_{i,c,t} = T_t \times E_{i,c,t} \tag{5}$$

Technology levels are the same for all local economies –the technology frontier is freely accessible. For simplicity, technology levels are the same for all sectors as well.[20] Thus, the source of heterogeneity in productivity across sectors and locations is $E_{i,c,t}$ (in the rest of this section and the next, which focus on a single local economy, I drop the subindex c to simplify notation).

Efficiency levels in the different sectors of the local economy are determined by local capabilities, under the presence of complementarities and cross-sector spillovers. These different elements, explained below, underlie the role of diversity captured in this model. A

[20] I will assume that the technological frontier moves at a constant rate g_T after industrial technologies become available at time zero (the onset of the "Second Industrial Revolution"). I will also assume $g_{\bar{w}_u} = g_{\bar{w}_s} = g_{T^{1-\alpha}}$, ensuring that wages and output per worker grow at the same rate in the steady state.

key assumption is that capabilities are not mobile across locations because the knowledge embedded in capabilities cannot be codified.[21]

Sector i requires a set of sector-specific capabilities indexed by $j_i = 1, ..., J_i$, each of which has its own efficiency level $e_{j_i t} \in [0, \bar{e}]$. Each capability can be thought of as a segment of the production process involving the application of a particular piece of knowledge. While some sectors may require only one or two capabilities, others may require several: J_i captures the level of *complexity* of sector i (as explained later, J_i is assumed to be positively related with skill-intensity).

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

$$E_{it} = \prod_{j=1}^{J_i} e_{j_i t} \ . \tag{6}$$

There are cross-sectoral spillovers within each local economy.[22] In particular, the efficiency of the local economy for a particular capability is given by the proximity of that capability to a previously established capability in some other sector of the economy – where "proximity" captures a notion of similarity in the knowledge space. The local economy will be inefficient at performing operations that are far from any operation that is already performed in the economy, but highly efficient at doing things that are close to something already done in the economy.

I use the following definitions and notation. The set of established capabilities at time t is denoted by $\mathbf{\Omega}_t$ (and its cardinality by Ω_t), while the set of capabilities in sectors other than i is denoted by $\mathbf{\Omega}_t^{i' \neq i}$ (and its cardinality by $\Omega_t^{i' \neq i}$). Incorporating the notion of cross-sector spillovers, local efficiency for capability j required by sector i is given by $e_{j_i t} = \bar{e} - d(j_i, \mathbf{\Omega}_{t-1}^{i' \neq i})$, where $d(j_i, \mathbf{\Omega}_{t-1}^{i' \neq i})$ is the minimum distance between that capability and an element of the set of previously established capabilities in other sectors.

I assume that the positions of capabilities in the knowledge space are independent draws from a uniform distribution on a circle with radius $\bar{e}/\pi$. Thus, the pdf of the minimum distance $d(j_i, \mathbf{\Omega}_{t-1}^{i' \neq i})$ of a capability and a previously existing one in some other sector is $f(d) = \Omega_{t-1}^{i' \neq i} \bar{e}^{-\Omega_{t-1}^{i' \neq i}} (\bar{e} - d)^{\Omega_{t-1}^{i' \neq i} - 1}$, and thus $E\left[d(j_i, \mathbf{\Omega}_{t-1}^{i' \neq i})\right] = \frac{\bar{e}}{\Omega_{t-1}^{i' \neq i} + 1}$. Distances between any two locations in the circle are between zero and $\bar{e}$, ensuring that $e_{j_i t} \in [0, \bar{e}]$.

[21]To make capabilites inmobile one also needs to assume that individual workers cannot take capabilities with them to different locations and that hiring groups of workers is not possible due to coordination problems.

[22]Scherer (1984) provides evidence on cross-industry technology flows, while Rosenthal and Stange (2004) review evidence pointing to the localized nature of knowledge spillovers.

Since the draws for the minimum distances corresponding to different capabilities required by a sector are independent, expected efficiency in sector i is given by

$$E(E_{it}) = E\left(\prod_{j}^{J_i} e_{j_i t}\right) = [E(e_{j_i t})]^{J_i} = \bar{e}^{J_i}\left[1 - \frac{1}{\Omega_{t-1}^{i' \neq i} + 1}\right]^{J_i} . \tag{7}$$

The elasticity of expected efficiency in sector i with respect to the number of previously existing capabilities in other sectors is

$$\eta_{E(E_{it}),\Omega_{t-1}^{i' \neq i}} = \frac{\Delta E(E_{it})/E(E_{it})}{\Delta \Omega_{t-1}^{i' \neq i}/\Omega_{t-1}^{i' \neq i}} .$$

The following two lemmas characterize how expected efficiency in a manufacturing sector depends on the number of established capabilities in other sectors.

Lemma 1. Expected efficiency in sector i is increasing in the number of previously existing capabilities in other sectors: $\eta_{E(E_{it}),\Omega_{t-1}^{i' \neq i}} > 0$.

Proof. See Appendix F.

The intuition behind Lemma 1 is that in a more diverse economic environment (i.e., one with a broader range of established capabilities) there is a higher likelihood of finding existing pieces of knowledge that are close to the ones required by any given sector. Lemma 2 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 capabilities in other sectors is increasing in the sector's complexity: $\Delta\eta_{E(E_{it}),\Omega_{t-1}^{i' \neq i}}/\Delta J_i > 0$.

Proof. See Appendix F.

Sectoral complexity (J_i) and skill-intensity (γ_i) are assumed to be positively related; formally, set $\gamma_i = G(J_i)$ with $\Delta G/\Delta J_i > 0$. We can think of the skill that defines skilled workers as general human capital that facilitates the understanding of connections between different segments of a productive process, which is more important in sectors where production involves a large number of segments. Consistent with this logic, each agricultural product, characterized by a simple production process that does not involve skilled labor, is assumed to require a single capability. Thus, the (exogenously determined) number of agricultural varieties in the local economy determines one-to-one the number of capabilities generated by agriculture, denoted by Ω^A.

6.3 The Mechanics of Entry and Structural Change

There is one potential entrant in each sector per period, and entrants that become producers retire after one period.[23] Setting up production is costly, as it requires learning a blueprint prescribed by the technology frontier and implementing it in the local economy.

The setup cost, $F_t = \psi T_t^{1-\alpha}$, increases in a lock-step fashion with the level of technology, reflecting that more advanced blueprints are costlier to implement. The minimum distances of required capabilities with respect to previously established ones become known only after the entrepreneur incurs the setup cost. In making the entry decision, the potential entrant –assumed to be risk neutral– only knows the expected level of efficiency.

A sector will be active if expected benefits are larger than the setup cost, which defines a threshold in expected efficiency above which entry takes place:

$$E(\Pi_{it}) > F_t \quad \Longleftrightarrow \quad E(E_{it}) > \widetilde{E}_{it} = \frac{\psi\left(\frac{w_{u,t}}{T_t^{1-\alpha}}\right)^{\frac{\alpha}{1-\alpha}}}{(1-\alpha)\left[(1-\gamma_i)\alpha\left(\frac{\gamma_i}{1-\gamma_i}\frac{w_{u,t}}{w_{s,t}}\right)^{\gamma_i}\right]^{\frac{\alpha}{1-\alpha}}} \; .$$

Assuming that $g_{\bar{w}_u} = g_{\bar{w}_s} = g_{T^{1-\alpha}}$, which ensures that wages and output per worker grow at the same rate in the steady state, the threshold in expected efficency is time-invariant: $\widetilde{E}_{it} = \widetilde{E}_i$.

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

$$\widetilde{\Omega}_i = \frac{1}{1 - \frac{\widetilde{E}_i^{1/J_i}}{\bar{e}}} - 1 \; .$$

If the number of previously established operations in other sectors is below the threshold, expected labor employed in sector i will be zero; if it is above the threshold, expected employment will be the optimal quantity derived before for active sectors. Thus,

$$E(L_{i,t}) = E(L_{i,t}^*) \times \mathbb{1}_{\left[\Omega_{t-1}^{i'\neq i} > \widetilde{\Omega}_i\right]} \; .$$

where $E(L_{i,t}^*) = E(L_{u,i,t}^* + L_{s,i,t}^*) = \left(1 + \frac{\gamma_i}{1-\gamma_i}\frac{w_u}{w_s}\right)\left[\frac{(1-\gamma_i)\alpha}{w_u}\left(\frac{\gamma_i}{1-\gamma_i}\frac{w_u}{w_s}\right)^{\gamma_i\alpha}\right]^{\frac{1}{1-\alpha}} E(A_i)$ is the expected optimal employment in an active sector, and $\mathbb{1}_{\left[\Omega_{t-1}^{i'\neq i} > \widetilde{\Omega}_i\right]}$ is an indicator function that takes a

[23] While these simplifying assumptions allow me to get a simple, closed-form solution to the model, the qualitatively results would hold under alternative assumptions.

value of one when the number of previously established operations in other sectors is above the threshold (i.e., the sector is active) and zero otherwise.

The following propositions describe how the set of established capabilities affects the expected composition of production in the local economy.

Proposition 1. The expected value of employment in active sector i is non-decreasing in the number of previously established capabilities in other sectors: $\eta_{E(L^*_{it}),\Omega^{i'\neq i}_{t-1}} \geq 0$.

Proof. Since $E(L^*_{it})$ is a linear function of $E(E_{it})$, we have that $\eta_{E(L^*_{it}),\Omega^{i'\neq i}_{t-1}} = \eta_{E(E_{it}),\Omega^{i'\neq i}_{t-1}}$. Thus, Proposition 1 follows directly from Lemma 1. □

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

Proof. Since $\eta_{E(L^*_{it}),\Omega^{i'\neq i}_{t-1}} = \eta_{E(E_{it}),\Omega^{i'\neq i}_{t-1}}$, Proposition 2 follows directly from Lemma 2. □

Propositions 1 and 2 (which describe the effects of diversity on sectoral employment levels) are straightforward implications of Lemmas 1 and 2 (which characterize the effects on sectoral efficiency levels). Beyond describing the impact on the composition of production, Proposition 2 suggests that under some conditions diversity can lead to higher average skill-intensity and output per worker in the local economy, since complex sectors have high values of γ_i (recall that $\frac{\partial h^*_i}{\partial \gamma_i} > 0$ and $\frac{\partial y^*_i}{\partial \gamma_i} > 0$).

While Propositions 1 and 2 characterize the effects of diversity in the set of established capabilities through the intensive margin (i.e., the volume of employment in active sectors), Proposition 3 refers to the the effects of diversity across all industrial sectors on the extensive margin (i.e., entry) (part a), and the intensive and extensive margins combined (part b).

Proposition 3. (*Industrialization*). (a) The number of active industrial sectors is increasing in the number of previously existing capabilities: $\Delta\sum_{i=1}^{I} \mathbb{1}_{\left[\Omega^{i'\neq i}_{t-1} > \tilde{\Omega}_i\right]}/\Delta\Omega_{t-1} \geq 0$; (b) The expected value of total industrial employment is non-decreasing in the number of previously existing operations: $\Delta E\left(\sum_{i=1}^{I} L_{it}\right)/\Delta\Omega_{t-1} \geq 0$.

Proof. See Appendix F.

6.4 The Evolution of Local Economies

The number of capabilities in period t is determined by the set of capabilities established in period $t-1$:

$$\Omega_t = \sum_{i=1}^{I} J_i \times \mathbb{1}_{\left[\Omega_{t-1}^{i' \neq i} > \widetilde{\Omega}_i\right]} + \Omega^A \tag{8}$$

To characterize the evolution of capabilities more precisely, start by noting that the collection of sector-specific thresholds can be arranged in increasing order. This increasing sequence defines a ranking of industrial sectors by their timing of entry. We can then use this ranking to define a new index spanning industrial sectors, $q = 1, ..., I$, where sectors with high q have high entry thresholds and thus enter production relatively late (if they do enter eventually). If there are sectors with the same entry threshold $\widetilde{\Omega}_i$, in the q-index they are assigned contiguous integers in arbitrary order. A sector with a high q never enters production before a sector with low q, though the two sectors may enter production in the same period even if they have different entry thresholds.[24]

By providing a timing-of-entry ordering of industrial sectors, the q-index helps to identify which sectors are *rest points* and characterize the evolution 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 $\sum_{q=1}^{m} J_q + \Omega^A < \widetilde{\Omega}_{m+1}$. Industrial sector $q = I$ is also defined as a *rest point.*

Let us empashize the intuition behind 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 capabilities is $\sum_{q=1}^{m} J_q + \Omega^A$. If this is below the threshold required to enter production in sector $m+1$ (denoted by $\widetilde{\Omega}_{m+1}$), then the process of structural change cannot go beyond sector m. Likewise, the process of structural change cannot go beyond sector $q = I$ (the one with the highest entry threshold), since if that sector becomes active there are no more inactive sectors to enter. When the local economy reaches a rest point, the process of structural change reaches an end.

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

[24] The number of capabilities may go from below the threshold of the low q sector to above the threshold of the high q sector in just one period as other sectors with lower q-index values become active.

the local economy. The sector defining the steady state is denoted by q^*, and the number of capabilities in the steady state is $\Omega^* = \sum_{q=1}^{q^*} J_q + \Omega^A$.

The process of structural change takes the economy to enter production in sector q^*, and that is the last sector to become active—the culmination of the local economy's development path. While the economy will continue to grow at a rate given by (exogenous) technological progress in the frontier, endogenous growth through diversification is shut down. Thus, the steady state is characterized by a constant growth rate and a stable composition of production.

The set of sector-specific entry thresholds with the ordering captured in the q-index, together with the number of agricultural capabilities, provide sufficient information to determine the steady state of the local economy. In turn, the equation for the number of capabilities at time t can be recasted using the q-index and discarding all sectors with $q > q^*$. This revised version of equation (5), which may labelled as the *capability formation function*, together with the initial condition (the number of capabilities before the onset of industrialization), provide a full characterization of the evolution of the local economy:

$$\begin{aligned} \Omega_t &= \sum_{q=1}^{q^*} J_q \times \mathbb{1}_{\left[\Omega_{t-1}^{q' \neq q} > \widetilde{\Omega}_q\right]} + \Omega^A \\ \Omega_0 &= \Omega^A \end{aligned} \tag{9}$$

To establish the effects of agricultural diversity on comparative economic development, consider N local economies that are identical in all respects but for their levels of agricultural diversity, i.e. they have different values of Ω_c^A, where the c subindex spans all the local economies under consideration.

Proposition 4. (*Comparative economic performance*). If a sector m is a rest point for a local economy s, then it is also a rest point for any local economy z with $\Omega_z^A < \Omega_s^A$. In the steady state, economy s has a (weakly) higher number of active industrial sectors and a higher number of established capabilities than any economy with lower agricultural diversity: $q_s^* \geq q_z^*$ and $\Omega_s^* > \Omega_z^*$.

Proof. If m is a rest point for economy s, this means that $\sum_{q=1}^{m} J_q + \Omega_s^A < \widetilde{\Omega}_{m+1}$. And since $\Omega_z^A < \Omega_s^A$, then $\sum_{q=1}^{m} J_q + \Omega_z^A < \widetilde{\Omega}_{m+1}$, which means that m is a 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. $q_s^* \geq q_z^*$; and thus we have that $\Omega_s^* = \sum_{q=0}^{q_s^*} J_q + \Omega_s^A > \sum_{q=0}^{q_z^*} J_q + \Omega_z^A = \Omega_z^*$ □

6.5 Numerical Illustration

I present a numerical illustration of the long-run effects of agricultural diversity by considering two economies that are identical in all respects but for their levels of Ω_c^A. A time period is one decade. The parameter values used in the simulation –intended to be reasonable without aiming for empirical accuracy– are displayed in Table 7 (growth rates are annualized). I assume that the technological frontier moves at a constant rate g_T after industrial technologies become available at time zero (the onset of the "Second Industrial Revolution").

Table 7. Parameter Values

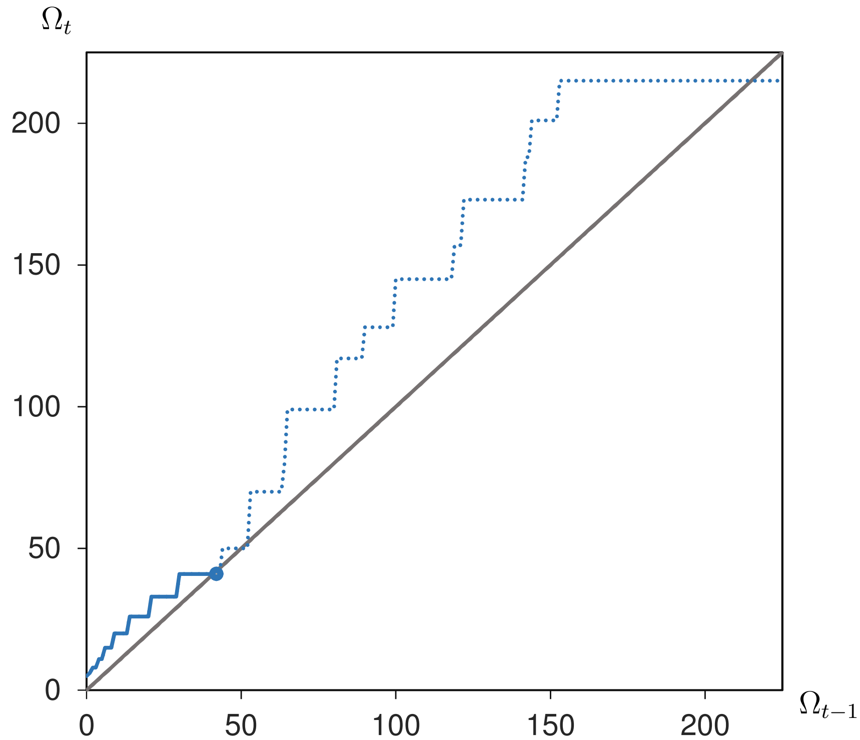
Parameter	Value
Total Agricultural Land, X	1
Agricultural technology, A_{a0}	10
Industrial technology term, $T_0^{1-\alpha}$	10
Wage of unskilled workers, w_{u0}	1
Wage of unskilled workers, w_{s0}	1.5
Industrial returns to scale, α	0.65
Land returns to scale, σ	0.65
Growth rates, $g_{T^{1-\alpha}}$, g_{A_a}, g_{w_s}, g_{w_u}	0.02
Entry cost parameter, ψ	2.5
Max operation efficiency, $\bar{e}$	1.01
Distribution of J_i	1 sector for each $J_i = 1, ..., 20$
γ_i	$1 - \frac{1}{J_i+1}$

Consider first local economy b, with $\Omega_b^A = 5$. The capability formation function corresponding to this initial level of diversity, given the parameter values, is displayed in Figure 10. The step function describing established capabilities crosses the 45° line for $\Omega_b^* = 40$; this is the steady state number of capabilities. The dotted line for numbers of capabilities $\Omega_b^* = 40$ corresponds to sectors beyond the steady state ($q_b^* = 8$), which cannot be reached.

The capabality formation function and the initial condition fully describe the evolution of the local economy over time:

$$\begin{aligned} \Omega_{b,t} &= \sum_{q=1}^{8} J_q \times \mathbb{1}_{\left[\Omega_{b,t-1}^{q' \neq q} > \widetilde{\Omega}_q\right]} + 5 \\ \Omega_{b,0} &= 5 \end{aligned} \tag{10}$$

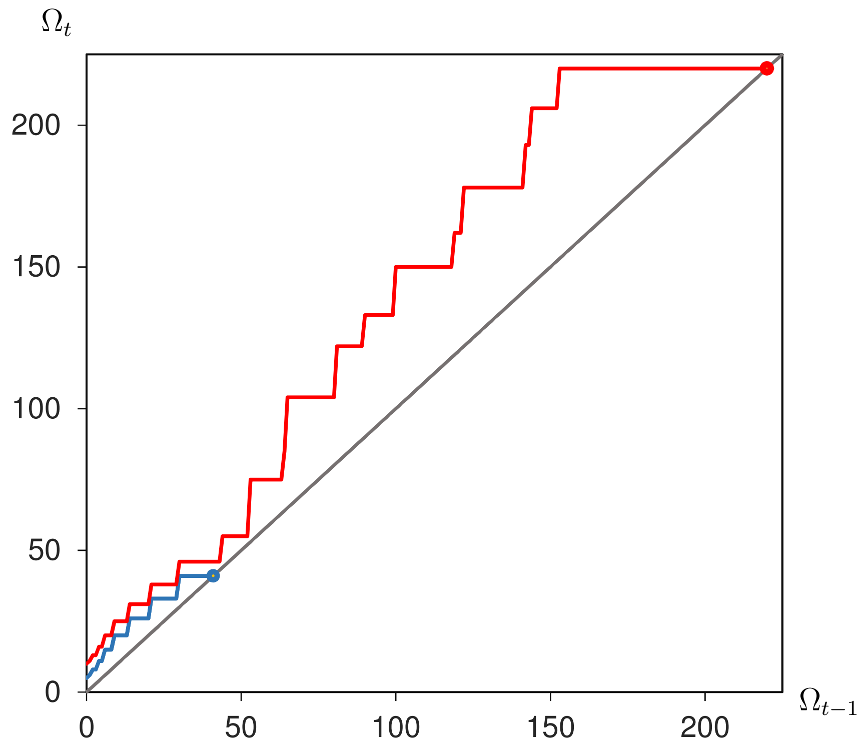
FIGURE 10. CAPABILITY FORMATION IN ECONOMY b (with $\Omega_b^A = 5$)



Consider now another local economy, r, for which the number of agricultural capabilities is $\Omega_r^A = 10$; for this local economy $\sum_{q=1}^{7} J_q + \Omega_r^A < \widetilde{\Omega}_8$, and so sector $q = 8$ is not a rest point. For economy r the capabilities formation function reaches all the way up to sector $q = I$, since there is no rest point before that last industrial sector. Figure 11 displays thecapabilities formation functions for the two local economies, capturing the divergence in their patterns of development that emerges in the critical juncture in which b reaches a rest point while r continues the process of structural change.

A full picture of comparative economic performance is displayed in Figures 12a to 12d. At time zero, at the onset of the industrialization process, the two economies exhibit only slight disparities; economy b enters production in two industrial sectors, while economy r takes its first step into industrialization with three sectors. They both acquire additional capabilities and go through a process of structural change in the following periods with only moderate differences of total capabilities, active industrial sectors, and overall industrialization (i.e. the share of workers employed in manufacturing). The gap in output per worker between the two economies (displayed in Figure 12d) opens up at time zero, but tends to be closed in the following decades.

Figure 11. Capability Formation in Economies b (with $\Omega_b^A = 5$) and r (with $\Omega_r^A = 10$)



A few decades into the industrialization process, a critical juncture is reached. Economy b reaches a rest point in sector $q_b^* = 8$, while economy r gets there with enough capabilities to enter production in sector $q = 9$, which induces the formation of new capabilites and enables a continued process of structural change. The gap in number of capabilities and active industrial sectors, as well as in overall industrialization and output per worker, drastically opens up subsequently, and it stabilizes only several decades after, when economy r reaches its steady state.

Figure 12a. Number of Established Capabilities

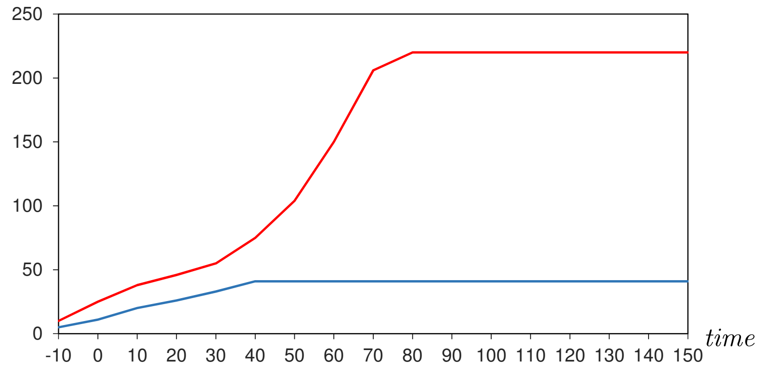


Figure 12b. Number of Active Industrial Sectors

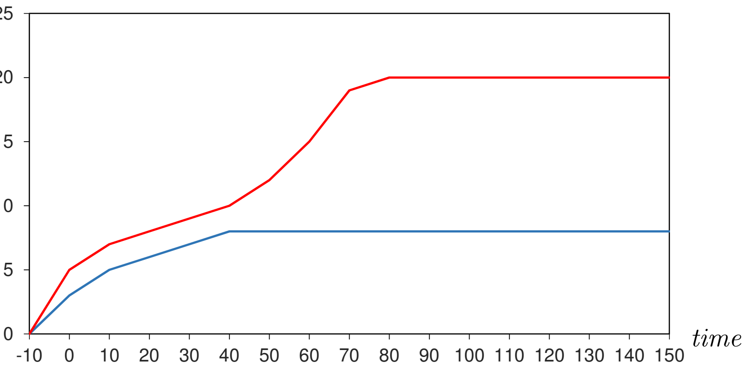


Figure 12c. Share of workers in manufacturing

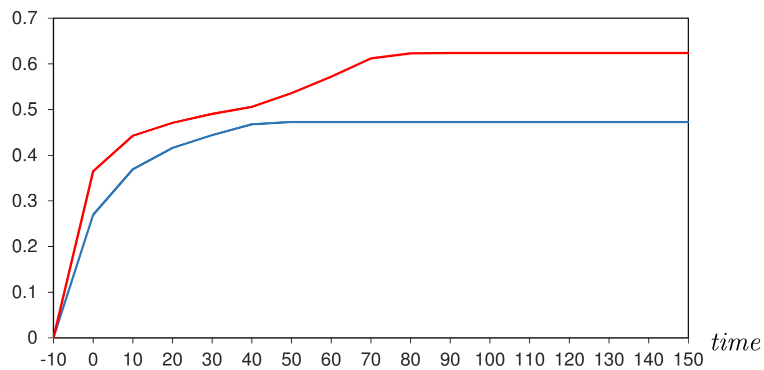
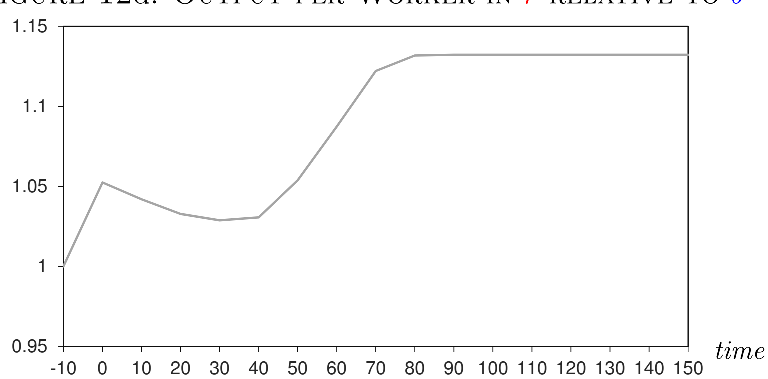


Figure 12d. Output per Worker in r relative to b



7 Other mechanisms

7.1 Agricultural Productivity

The literature on structural change has devoted considerable attention to the relative importance of manufacturing productivity growth and agricultural productivity growth as drivers of industrialization (e.g., Alvarez-Cuadrado and Poschke, 2011). Section 4 shows that early agricultural diversity was conducive to productivity growth in the manufacturing sector, which would *pull* labor out of agriculture. Was industrialization also fostered by a positive effect of agricultural diversity on agricultural productivity that *pushed* labor out of agriculture? Or maybe diversity negatively affected productivity, and agricultural productivity was actually bad for industrialization?

For an agricultural productivity channel to be operative, two links in the causal chain have to be in place—the effect of agricultural diversity on agricultural productivity and the effect of the latter on industrialization have to be significant, and they need to have the same sign. This subsection discusses how those links may operate and examines each of them empirically in the context under examination. Overall, 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 innovation and adoption of new techniques. On the other hand, diversity may imply foregoing gains from specialization due to product-specific economies of scale.

Panel A of Table 8 shows IV estimates of the effects of agricultural diversity on agricultural productivity in 1920 (as measured by the natural log of farm output per acre). Although the point estimates are positive, the estimates do not indicate a significant effect of agricultural diversity on productivity levels in 1920.

How would agricultural productivity, in turn, affect industrialization? Agricultural productivity growth may be a necessary condition for a successful take-off. Higher agricultural productivity can release labor to be employed in manufacturing; it means cheaper food for workers and cheaper inputs for firms; it creates resources for investment, which can be channeled towards industrial capital formation; it also means higher purchasing power and thus higher demand for local manufacturing production.[25] 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 could hold back that effect.

Panel B of Table 8 shows IV estimates of the effects of agricultural productivity in 1860 on the share of population employed in manufacturing in 1920. The IV estimates use the max and average of (normalized) attainable yields for the five major agricultural products as instruments for actual agricultural productivity. The results are not robust across specifications.

Table 8. Agricultural diversity, agricultural 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, 1920*						
Agri.Diversity$_{1860}$	0.579	0.648	0.270	0.669	0.421*	1.216
	(0.387)	(0.442)	(0.222)	(0.608)	(0.241)	(1.080)
R^2	0.018	0.017	0.464	0.460	0.506	0.489
Panel B. *Dependent variable: Share of population in manufacturing, 1920*						
Ln Farm Productivity$_{1860}$	0.0156***	-0.0141	0.0135**	-0.0180	0.00587	0.00480
	(0.00522)	(0.0177)	(0.00512)	(0.0218)	(0.00479)	(0.0357)
R^2	0.383	0.03	0.413	0.08	0.519	0.237
State FE	N	N	Y	Y	Y	Y
Ecological controls	N	N	Y	Y	Y	Y
Distances to water and cities	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: See Appendix A for variable definitions and sources. Robust standard errors clustered at the state level are reported in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

Overall, the results presented in Table 8 do not support the relevance of the agricultural productivity channel, since none of the two links in the causal chain receives strong empirical support.

[25]See, e.g., Johnston and Mellor (1961). An early proponent of the complementarity between agricultural and industrial activities was Alexander Hamilton, who wrote in his 1791 *Report on Manufactures* that “the *aggregate* prosperity of manufactures, and the *aggregate* prosperity of Agriculture are intimately connected” (quoted by Olmstead and Rhode, 2009).

7.2 Volatility, Risk and Local Financial Development

The basic idea that diversification dampens the effects of negative sector-specific shocks goes back to Marshall (1895), who noted that "a district which is dependent chiefly on one industry is liable to extreme depression, in case of a falling-off in the demand for its produce, or of a failure in the supply of the raw material which it uses." A positive relationship between diversity and income levels operating through reduced risk and volatility appears in some recent theoretical contributions reviewed in section 2 (see Acemoglu and Zilibotti, 1997; Koren and Tenreyro, 2013).

Through its relationship with risk, diversity could affect the development of local financial institutions, which may in turn affect development through channels other than risk management (e.g., the channeling of savings to investment). Diversity may increase credit supply insofar as it allows local banks to reduce risk exposure by funding a wide array of imperfectly correlated projects (see Ramcharan, 2010b, who calls this the "production structure hypothesis").

On the other hand, places that were not well-suited to limit volatility through diversification may have had higher demand for financial intermediation. Higher volatility could also foster mutual insurance arrangements and social trust (Durante, 2009). Thus, volatility could have positive effects through endogenous financial development and social norms, especially in an epoch of rapid change like the Second Industrial Revolution.

I begin by assessing the idea that under incomplete financial markets volatility may hinder the emerging industrial sector. I construct a measure of predicted volatility using the mix of agricultural products of each county predicted by the FML model and the year-to-year evolution prices at the country level from 1866 to 1919 for 16 products that account for over 93% of total agricultural output in 1860 in my sample. Keeping the predicted shares of products fixed, I calculate the value of counties' agricultural output in each year as $y^{\mathrm{a}}_{ct} = \sum_i \hat{\theta}_{ic} p_{it}$, and then calculate the average annual growth rate Gy^{a}_{ct} and its standard deviation, $St.Dev.(Gy^{\mathrm{a}}_{ct})$.

Constructed in that way, $Std.Dev.(Gy^{\mathrm{a}}_{ct})$ is an exogenous predictor of the volatility of agricultural output value growth induced by the volatility of macro prices. This indicator of agricultural volatility is negatively correlated with initial diversity (the correlation in this sample is -0.34), but it also depends on the particular mix of agricultural products of each country and on the covariances of price changes.[26]

[26] The main result (that the possitive effects of diversification are not accounted for by volatility reduction) also holds for other measures of volatility. In particular, I consider alternative measures to address different concerns: (1) if changes in prices reflect supply shocks rather than demand shocks, the baseline measure of volatility may not be exogenous; to capture for macro supply shocks, I combine the price data with national

To assess the relevance of the mechanism under consideration, I include the county-level mean and standard deviation of Gy^{a}_{ct} in the same specifications considered before. Table 9 reports the results of these estimations. To facilitate comparison, the results without including these additional regressors are reproduced in the same table.

Table 9. Assessing the Risk and Volatility Channel

	Dependent variable: Ln Manufacturing labor productivity 1920					
	Specification 1		Specification 2		Specification 3	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. OLS estimates						
Agri.Diversity$_{1860}$	0.470***	0.778***	0.275***	0.365***	0.277***	0.362***
	(0.113)	(0.185)	(0.0910)	(0.112)	(0.0845)	(0.125)
$St.Dev.(Gy^{\mathrm{a}}_{ct})$		0.574**		0.167		0.249
		(0.246)		(0.126)		(0.153)
R^2	0.029	0.066	0.255	0.259	0.277	0.280
Panel B. IV estimates						
Agri.Diversity$_{1860}$	0.877***	1.583***	0.414**	0.770**	0.568**	0.882**
	(0.214)	(0.328)	(0.206)	(0.380)	(0.253)	(0.449)
$St.Dev.(Gy^{\mathrm{a}}_{ct})$		1.353***		0.500		0.653
		(0.390)		(0.323)		(0.404)
R^2	0.007	0.038	0.255	0.255	0.268	0.271
State FE	N	N	Y	Y	Y	Y
Ecological controls	N	N	Y	Y	Y	Y
Distances to water and cities	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: Gy^{a}_{ct} is the mean annual growth of $y^{\mathrm{a}}_{ct} = \sum_i \hat{\theta}_{ic} p_{it}$, a predictor of the value of agricultural output constructed with predicted shares for 1860 and subsequent national prices. $St.Dev.(Gy^{\mathrm{a}}_{ct})$ is its standard deviation. See Appendix A for other variable definitions and sources. Robust standard errors clustered at the state level are reported in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

The theories suggesting that diversity has positive effects by reducing volatility would predict a negative effect of $St.Dev.(Gy^{\mathrm{a}}_{ct})$ on manufacturing productivity and a reduction

data on yields per acre, and construct a measure with macro prices times productivities for 11 crops that cover around 70% of agricultural production; (2) I construct adjusted volatility measures to avoid bias due to heterogeneity in the percentage of production for which data is unavailable by making some assumptions about the mean, standard deviation and correlation of price changes for products with missing data; (3) I consider alternative price deflators.

of the magnitude of the coefficient on agricultural diversification when $St.Dev.(Gy^{\mathrm{a}}_{ct})$ is included as control. If that was the only channel through which agricultural diversity affects development, the coefficient on agricultural diversity should drop to zero.

The results are not in line with those predictions. The estimated effect of volatility is not negative and the estimated coefficient on initial diversification is not reduced, so this channel does not seem to account for the positive effects of agricultural diversity. The estimated effect of volatility is actually positive (though not consistently significant) and the estimated coefficients on diversity actually increase when including the measure of predicted volatility (though this is not always the case when alternative measures of volatility are considered; see footnote 25). Although not fully robust for all specifications and volatility measures, these results suggest that volatility may actually have positive effects.

The idea that diversity may affect financial development (either negatively through credit demand or positively through credit supply) is not supported by the evidence. Table 10 presents estimates of the effects of volatility on county-level bank density (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 (see section 7.3).

Table 10. 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)
Agri.Diversity$_{1860}$	0.00801	0.0321	-0.0400	0.110	-0.0618	-0.111
	(0.157)	(0.333)	(0.0696)	(0.159)	(0.0530)	(0.0922)
State FE	N	N	Y	Y	Y	Y
Ecological controls	N	N	Y	Y	Y	Y
Distances to water and cities	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	0.000	0.000	0.658	0.090	0.705	0.219

Notes: See Appendix A for variable definitions and sources. Robust standard errors clustered at the state level are reported in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

7.3 Land Concentration and Local Institutions

Agricultural diversity may have affected the manufacturing sector by molding the distribution of land ownership. If there are product-specific fixed costs (e.g., crop-specific skills or capital) or other sources of increasing returns to scale, then places with low potential diversity (high relative productivity for one or a few products) would tend to have larger farm sizes than places with low potential diversity. In addition, if economies of scope decline with size, the benefits of farm-level diversification are higher for small farms (Chavas and Aliber, 1993), and thus places with high potential diversity may be more conducive to small farms.

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 and Ramcharan, 2011), thus negatively affecting the dynamics of industrialization. Galor et al. (2009) provide a panel data analysis at the US 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 the transition from agriculture to modern industry. Ramcharan (2010a) and Vollrath (2013) provide evidence to the same effect from US county-level data during the same period.

Rajan and Ramcharan (2011) argue that landed elites can hinder the development of local banks to mantain their power. Their paper shows, also for the early 20th century US, that in counties with higher land inequality there were fewer banks per capita and credit was costlier and more limited. Even if large landowners did not operate against financial develpoment, high land inequality could imply that many prospective borrowers had limited access to credit due to insufficient collateral (e.g., Chakraborty and Ray, 2007).[27]

Did agricultural diversity lower land concentration? Panel A of Table 11 shows estimates of the effects of agricultural diversity in 1860 on the share of farmland corresponding to farms larger than 500 acres in 1920.[28] On average, farms this large represented around 1.5% of farms and 10% of farmland, but these figures were much larger in some counties; farms over 500 acres accounted for more than 50% of farmland for 20 counties in the sample, most of them in Texas, Louisiana and Georgia, which had very large predicted and actual shares of production in wool, cane sugar, and rice, respectively. The results show that higher levels

[27]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 US counties.

[28]Results are similar, but not robust across specifications, if the outcome variable is the share of land corresponding to other size thresholds, or the share corresponding to the largest 5%, 10% or 20% of farms.

of diversity are associated with lower levels of land concentration.

Given its negative effect on land concentration, agricultural diversity may have favored local school expenditures and/or financial development through the mechanisms discussed above. However, section 7.1 shows no significant effects of early agricultural diversity on bank density in 1920. Likewise, the evidence does not support the idea that it may have positively affected educational investments.[29] Panels B and C of Table 11 show results from regressions of school expenditures per capita in 1890 and 1932, respectively, on agricultural diversity in 1860. The sign and significance of the estimates are not robust.

Table 11. Effects of Agri.Diversity on Land Inequality 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 farms over 500 acres 1920*						
Agri.Diversity$_{1860}$	-0.319***	-0.304***	-0.169***	-0.158***	-0.141**	-0.179
	(0.0715)	(0.0741)	(0.0336)	(0.0534)	(0.0535)	(0.116)
R^2	0.152	0.152	0.564	0.564	0.636	0.634
Panel B. *Dependent variable: School expenditures per capita, 1890*						
Agri.Diversity$_{1860}$	1.058***	2.100***	0.0212	-0.186	0.112*	-0.269
	(0.255)	(0.458)	(0.0774)	(0.151)	(0.0656)	(0.250)
R^2	0.106	0.003	0.866	0.137	0.879	0.203
Panel C. *Dependent variable: School expenditures per capita, 1932*						
Agri.Diversity$_{1860}$	-0.494*	-0.283	-0.461	-0.291	-0.167	-0.272
	(0.256)	(0.444)	(0.272)	(0.622)	(0.248)	(1.078)
R^2	0.009	0.007	0.237	0.038	0.294	0.109
State FE	N	N	Y	Y	Y	Y
Ecological controls	N	N	Y	Y	Y	Y
Distances to water and cities	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: See Appendix A for variable definitions and sources. Robust standard errors clustered at the state level are reported in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

[29] The absence of robust evidence regarding an effect of agricultural diversity on school expenditures may seem to contradict the previously established effects of diversity on the formation of specific skills and literacy. However, formation of specific skills may have taken place outside public schools; moreover, higher demand for general human capital may have been satisfied without increasing local school expenditures. In accordance with the model proposed in section 6, skill formation may have been attained through immigration.

8 Conclusion

This paper shows that agricultural production patterns preceding the onset of the Second Industrial Revolution had long-run effects on development across US counties. According to IV estimates, a one-standard-deviation increase in agricultural diversity in 1860 led to gains of around 5% in income per capita in recent decades. The positive effect of diversity in 1860 can be traced back to the advance of the industrialization process over the Second Industrial Revolution. Thus, the evidence suggests that early agricultural diversity affected long-run development by shaping local patterns of structural change during a period of rapid transformation in the US economy.

The correlations between agricultural diversity in 1860 and development outcomes are robust to the inclusion of an extensive set of controls. State fixed effects allow me to control for state-level institutions and policies as well as other sources of heterogeneity across counties that are constant within each state. Different measures of land productivity are included to ensure that the coefficient on diversity does not pick up the effects of agricultural resource abundance. I also control for specific specialization patterns with alternative sets of variables capturing the dominance of particular agricultural products. The inclusion of distances to major urban centers and waterways as well as access to railroads and a measure of market potential aims to ensure that the estimated relationship between agricultural diversification and development is not driven by the extent of potential gains from trade. A host of additional socio-economic controls capturing levels of development in 1860 are also included in one of the specifications.

The empirical strategy proposed to identify the causal effect of diversity exploits exogenous variation in agricultural diversity generated by climatic features. Using measures of potential productivity for different crops based on climate data, I estimate a fractional multinomial logit model and then construct an index of potential agricultural diversity. With an IV strategy based on this index (which explains a large fraction of the variation in actual diversity), I provide estimates of the causal effects of agricultural diversity on income per capita as well as on different intermediate variables through which it may have affected the process of development.

The evidence suggests that early agricultural diversity increased the relative size and productivity of the industrial sector by fostering the diversity of manufacturing inputs and skills, the formation of novel productive capabilities, and technological progress. The positive and significant effects of agricultural diversity on intermediate variables capturing these channels is consistent with the relevance of complementarities and cross-sector spillovers. I provide further support for the plausibility of the proposed mechanisms by testing a cross-county cross-industry implication: diversity in agriculture had a positive differential impact on skill-intensive and knowledge intensive industrial sectors.

To sharpen the interpretation of the findings, I propose a multi-sector endogenous growth model that highlights the interconnected roles of complementarities and cross-sector spillovers in the mechanics of structural change. The model generates not only a positive effect of diversity on industrialization, but also a differential effect on relatively complex industrial sectors. In addition, it explains why agricultural diversity can have long-run effects that unfold over time.

The evidence does not support the relevance of other mechanisms. The results regarding the role of agricultural productivity make it an implausible channel, thus highlighting the cross-sectoral character of the effects of agricultural diversity. To assess the possibility that agricultural diversity may have boosted economic performance by reducing volatility, I construct a measure of predicted volatility in the value of agricultural production based on its predicted composition and the evolution of prices at the national level. The results are not consistent with this channel. I also assess political economy mechanisms that may have operated at the local level. I find a negative effect of early agricultural diversity on land concentration, but no evidence of impacts on local financial development nor on local educational expenditures.

This paper adds to the literature on the deeply-rooted determinants of comparative development by showing that agricultural resource endowments and the composition of agricultural production at early stages of development can affect long-run economic performance. Beyond shedding new light on the role of agriculture in economic development, the paper may inform future contributions in the literature on growth and structural change. The evidence regarding the long-run effects of agricultural diversity suggests that the analysis of complementarities and linkages in models with finer levels of aggregation than standard two- or three-sector frameworks can yield new insights about the development process. The insights obtained from the history of US counties going back to 1860 may be relevant for understanding the growth trajectories of developing countries. To further our understanding of the role of diversity and establish policy implications, future research should attempt to pin down as precisely as possible the mechanisms through which diversity affects development in different contexts across space and time.

Appendix A. Data

Definitions and Sources

Outcome variables

Share of Population in Manufacturing. Total manufacturing workers over total population. Digitized US Census data are taken from NHGIS, for 1860-1940. Data for 1940 onwards are from digitized County Data Books compiled by the U.S. Census Bureau and available from Haines and ICPSR (2010).

Income per capita. Ln (1+income/population). Data on personal income and population in 1970, 1980, 1990 and 2000 is obtained from the Bureau of Economic Analysis. Pre-1960 income date are not available; as proxies, I use the sum of manufacturing and agricultural output for 1860-1940 (data taken from NHGIS), and for income per capita in 1950 I use median family income over average family size (data from digitized County Data Books compiled by the U.S. Census Bureau and available from Haines and ICPSR (2010)).

Manufacturing value added per worker. Ln (1+total manufacturing value added / total manufacturing workers). Digitized US Census data are taken from NHGIS, for 1860-1940. Data for 1940 onwards are from digitized County Data Books compiled by the U.S. Census Bureau and available from Haines and ICPSR (2010).

Manufacturing average wage. Ln (1+total wages in manufacturing / total manufacturing workers). Digitized US Census data are taken from NHGIS, for 1860-1940. Data for 1940 onwards are from digitized County Data Books compiled by the U.S. Census Bureau and available from Haines and ICPSR (2010).

Industrial sectoral diversification. An index defined as 1 minus the Herfindahl index of manufacturing employment shares across 59 different sectors in total manufacturing employment. County level employment data is constructed from microdata from US censuses obtained from Ruggles et al. (2010). Data for 1860, 1870, 1900 and 1920 are from 1-in-100 samples; data for 1880 are from a 10-in-100 sample.

Industrial skill diversity. An index defined as 1 minus the Herfindahl index of manufacturing employment shares in each of 75 different white collar and blue collar occupations and a 76th category for all unskilled workers. County level employment data is constructed from microdata from US censuses obtained from Ruggles et al. (2010). Data for 1860, 1870, 1900 and 1920 are from 1-in-100 samples; data for 1880 are from a 10-in-100 sample.

New Skills. Number of occupations present (i.e., with strictly positive number of workers) at the county-level among a subset of consists of 26 occupations for which the number of respondents in the Census microdata samples is either zero in 1860 or increased by over a factor of 50 from 1860 to 1920. County level employment data is constructed from microdata from US censuses obtained from Ruggles et al. (2010). Data for 1860, 1870, 1900 and 1920 are from 1-in-100 samples; data for 1880 are from a 10-in-100 sample. The 26 occupations are the following: aeronautrical engineers, chemical engineers, electrical engineers, industrial engineers, metallurgical engineers, mining engineers, engineers (n.e.c.); cement and concrete finishers; cranemen, derrickmen, and hoistmen; locomotive engineers; decorators and window dressers; electricians; excavating, grading, and road machinery operators; heat treaters, annealers, temperers; metal job setters; telegraph, telephone and power linemen and servicemen; loom fixers; airplane mechanics and repairmen; automobile mechanics and repairmen; office machine mechanics and repairmen; radio and television mechanics and repairmen; railroad and car mechanics and repairmen; motion picture projectionists; printing pressmen and plate printers; tool makers, die makers, and setters.

Literacy. Population 21+ who can read and write / Population 21+. Digitized US Census data are taken from NHGIS, for 1860-1940.

Patents per 1,000 inhabitants. 1000 * Patents filed county's inhabitants / Population. Patent data, reporting the location of each innovator, was compiled by Akcigit et al. (2013) from the US Trade and Patents Office. I am very grateful to the authors for sharing their data. To calculate patents per 1,000 inhabitants, I consider the location (latitude and longitude) given for each patent in the dataset and the boundaries of 1860 counties. I construct these variable for each decade, 1860-1869, 1870-1879,..., 1910-1919, and population levels at the beggining of each decade (US Census data taken from NHGIS).

Share of county's manufacturing workers employed in industrial sector s. Workers in sector s/ Total manufacuring workers in the county. County level employment data is constructed from microdata from US censuses obtained from Ruggles et al. (2010). Data for 1860, 1870, 1900 and 1920 are from 1-in-100 samples; data for 1880 is from a 10-in-100 sample.

Ln Farm Productivity. Ln (1+Total Farm Output/Total Acres). Source: digitized US Census data taken from NHGIS.

Bank density. Total number of banks over total population. FDIC data obtained from NHGIS.

Share of farmland in farms over 500 acres. Farmland in farms of size greater than 500 acres over total county farmland. Source: digitized US Census data taken from NHGIS.

School expenditures per capita. School government cost payments operations and maintenance over total population. Source: Rhode and Strumpf (2003).

Ecological controls

Land suitability for cultivation. County-level average of an index of land suitability for cultivation, to be interpreted as the probability that a given area is cultivated. Data source: Ramankutty et al. (2002).

Potential productivity measures for major products. Maximum and average of normalized attainable yields corn, cotton, hay, and wheat, and for grazing suitability. The normalization consists in dividing all product specific values for the the max attained in the sample before. Data sources: FAO-GAEZ and Erb et al. (2007).

Mean annual temperature. County-level average annual temperature measured in Celsius degrees. Data source: FAO-GAEZ.

Terrain elevation. County-level average terrain elevation measured in km. Data source: FAO-GAEZ.

Latitude. Absolute latitudinal distance from the equator in decimal degrees, calculated from the centroid of each county using ArcGIS and NHGIS county shapefiles.

Longitude. Absolute longitudal distance from the Greenwhich meridian in decimal degrees, calculated from the centroid of each county using ArcGIS and NHGIS county shapefiles.

Area. Surface area in 1000's of sq. km, calculated with NHGIS county shapefiles using ArcGIS.

Distances to water and cities

Distances to major urban centers: Distances in km (in logs) to New York, Chicago, Boston, Philadelphia and New Orleans, calculated from the centroid of each county using ArcGIS and NHGIS county shapefiles.

Distance to waterways: Minimum distances to a point in the the Coastline or the Great Lakes in km (in logs), calculated from the centroid of each county using ArcGIS and NHGIS county shapefiles.

Crop-specific controls

Dummies for dominance of major agricultural products: five dummies (for corn, cotton, animals slaughtered, hay, wheat) that take a value of 1 when the product has the largest share in a county's agricultural production. The data on agricultural production comes from digitized US Census data taken from NHGIS.

Share of plantation crops. Share of cotton, sugar, rice, tobacco, coffee, combined, in total agricutural output. Data source: digitized US Census data taken from NHGIS.

Socio-economic controls

Urbanization rate. Urban population / Total Population. Data source: digitized US Census data taken from NHGIS.

Population size Ln (Total Population). Data source: digitized US Census data taken from NHGIS.

Farm output. Ln (1+Total Farm Output/Total Acres). Data source: digitized US Census data taken from NHGIS.

Share of the population below 15 years. Population below 15 years / Total Population. Data source: digitized US Census data taken from NHGIS.

Share of the population 65+ years. Population 65+ years / Total Population. Data source: digitized US Census data taken from NHGIS.

Share of slaves in the population. Slave Population / Total Population. Data source: digitized US Census data taken from NHGIS.

Access to railroads. A dummy variable indicating whether the was a railroad in the county. Source: Haines and ICPSR (2010).

Market Potential. Following the classic definition of Harris (1954), market potential in county c is given by $\text{Market}_c = \sum_{k \neq c} d_{c,k}^{-1} N_k$, where k is the index spanning neighboring counties, $d_{c,k}$ is the distance between county c and county k, and N_k is the population of county k (here, in 1860). Population data are taken from NHGIS.

Measures of Complexity of Industrial Sectors

Skill-intensity. Average educational level of the industry's workers as reflected by IPUMS EDSCOR50 variable, which indicates the percentage of people in the respondent's occupational category who had completed one or more years of college. Constructed from microdata from US censuses obtained from Ruggles et al. (2010).

Industry knowledge-intensity. Percentage of engineers and scientists in total industry employment in the US economy in 1950. Constructed from microdata from US censuses obtained from Ruggles et al. (2010).

FAO Potential Productivity Data for Agricultural Products

The FAO's Global Agro-Ecological Zones project (GAEZ) v3.0 constructed crop-specific measures of attainable yields using climatic data (including precipitation, temperature, wind speed, sunshine hours and relative humidity) –based on which thermal and moisture regimes are determined– together with crop-specific measures of cycle length (i.e. days from sowing to harvest), thermal suitability, water requirements, and growth and development parameters (harvest index, maximum leaf area index, maximum rate of photosynthesis, etc). Combining all these data, the GAEZ model determines the maximum attainable yield (measured in tons per hectare per year) for each crop in each grid cell of 0.083x0.083 degrees. I use agro-climatic yields for intermediate levels of inputs/technology and rain-fed conditions for barley, buckwheat, cotton, maize, oats, pasture grasses, pasture legumes, alfalfa, potato, sweet potato, rye, cane sugar, tobacco, rice, wheat, tomato, carrot, cabagge, onion, pulses, sorghum, and flax.

Data on grazing suitability comes from Erb et al. (2007), who provide a world map with grid cells of 0.083x0.083 degrees classified into four grazing suitability classes. To calculate mean county-level grazing suitability, I assign to their four grazing suitability classes (which go from "least suitable class" to "best suitable class") consecutive integer values from 1 to 4, and a value of zero to the grid cells that they report as not suitable. Finally, the general measure of land suitability for cultivation –to be interpreted as the probability that each grid cell will be cultivated– is constructed by Ramankutty et al. (2002) for grid cells of 0.5x0.5 degrees.

Adjustment for changes in county borders

The units of observation throughout the paper are US counties as defined in 1860. At that time, most of the Western states were still territories and had only started to be partitioned into counties. In most territories there were only a few large counties, and county boundaries changed dramatically in the subsequent decades. To restrict the analysis to established states and counties whose boundaries remained relatively stable (as discussed below), I drop from the sample all of the Western US, plus Dakota Territory, Kansas Territory, Nebraska Territory and Indian Territory (later Oklahoma). Some other counties are also dropped because of missing data.[30] Most of the empirical analysis is conducted on the sample of 1,821 counties displayed in gray in Figure A1.

Among the counties in the sample (defined in 1860), over 70% did not experience subsequent changes in boundaries, and only 10% have overlaps of less than 80% in terms of area with a county defined in 2000. In this sense, boundaries were relatively stable for counties in the sample.

[30] After dropping counties in the West and the territories mentioned before, there remain 1907 counties in the sample, of which 85 are subsequently dropped for lack of data for key historical variables. Washington D.C. is also dropped from the sample, as it has missing data for some control variables and would not have any effects in any estimation that includes state fixed effects. Independent cities are considered as part of their containing/adjacent county.

Figure A1. Continental US counties, 1860

Boundary changes need to be taken into account to have consistent units of observation. To accomplish this, I use geographic shapefiles of county boundaries obtained from NHGIS and—with the help of GIS software—I determine the county defined in 1860 that contained each county or county fragment defined in 2000, discarding all fragments with less than 1 square mile. Then I calculate the values of variables measured in 2000 corresponding to counties defined with 1860 boundaries by assigning values from variables for 2000 in proportion to the area of the county defined in 2000 that each county defined in 1860 represents. I do exactly the same for all variables for periods after 1860 using the shapefiles of county boundaries for the corresponding decade. This procedure would be fully accurate if the quantities measured in aggregate variables were uniformly distributed over space.

Appendix B. Agricultural specialization patterns and development

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

The detrimental effects of the cotton slave economy in the U.S. South have been emphasized very often, but other contributions highlight the effects of specialization in other crops through different mechanisms. Earle and Hoffman (1980) pointed out that wheat, corn and livestock had highly seasonal labor requirements and thus specialization in those products implied that there was cheap labor available for the nascent industrial sector. Somewhat similarly, Goldin and Sokoloff (1984) argued that the relative productivity of women and children in hay, wheat and dairy was much lower than in plantation crops, thus implying that industries located in regions specialized in the former set of products could hire labor at lower cost. 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.

This paper highlights the effects of diversity in the agricultural production mix beyond any particular specialization pattern. As discussed in section 3, the diversity index can be highly correlated with the shares of dominant crops in production. To avoid confouding the effects of agricultural diversification with those of specialization in particular crops, I include crop-specific controls dummies for the 5 major agricultural products (these take a value of 1 when the product has the largest share in a county's agricultural production). This appendix shows that the qualitative results on the effects of diversity hold if I control for dominance dummies differently defined or for the actual shares of those 5 products.

Table B1 shows OLS and IV estimates of the effects of agricultural diversity on income per capita 2000 with alternative sets of crop-specific controls.[31] To facilitate comparison, columns 1-2 do not include any crop-specific controls, while columns 3-4 include the dominance dummies as defined before. Columns 5-6 include dominance dummies that take a value of 1 when the share for the corresponding crop in the county's agricultural output is

[31] Only agricultural diversification is instrumented in these IV regressions; the results are qualitively the same if the actual dominance dummies or shares are replaced by the corresponding values based on predicted shares based on the FML model estimates.

above 25%. Columns 7-8 include dominance dummies that take a value of 1 when the share for the corresponding crop is above the 75th percentile of the distribution of that share in the whole sample. Finally, columns 9-10 include the actual shares of each of the 5 major agricultural products.

The results confirm that agricultural diversity had positive effect on economic development. There is no compelling evidence of significant effects of specialization in any of the major agricultural products. The coefficients for all the variables capturing specialization in cotton get negative point estimates, but they never appear as significant at usual confidence levels. Specialization in wheat seems to have had positive effects on income per capita in 2000, although not robust for different specifications of the crop-specific controls. The absence of robust significant effects of specific specialization patterns in these cross-county regressions with state fixed effects should not be seen as contradicting the contributions mentioned above, which advance explanations about comparative development for larger regions. For the purposes of this paper, the important feature of this set of results is that the estimated coefficients for agricultural diversification remain consistently positive and significant across specifications with different crop-specific controls.

Table B1. The Effects of Agricultural Diversity versus Specific Specialization Patterns

	Dependent variable: Ln Income per capita, 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)
Agri.Diversity$_{1860}$	0.333***	0.395***	0.323***	0.342**	0.294***	0.331**	0.328***	0.341**	0.264***	0.284*
	(0.0564)	(0.0918)	(0.0607)	(0.140)	(0.0621)	(0.144)	(0.0680)	(0.142)	(0.0796)	(0.168)
Corn			-0.0249	-0.0261	-0.0358*	-0.0335	-0.0122	-0.0125	-0.130	-0.110
			(0.0317)	(0.0304)	(0.0184)	(0.0224)	(0.0183)	(0.0167)	(0.108)	(0.104)
Cotton			-0.0507	-0.0506	-0.0395	-0.0397	-0.0366	-0.0361	-0.130	-0.110
			(0.0546)	(0.0534)	(0.0339)	(0.0326)	(0.0324)	(0.0328)	(0.118)	(0.141)
Animals Slaughtered			-0.0665	-0.0685	-0.0304**	-0.0331**	-0.0292	-0.0299	0.170	0.198
			(0.0460)	(0.0469)	(0.0134)	(0.0157)	(0.0228)	(0.0253)	(0.125)	(0.127)
Hay			0.0455	0.0444	0.00895	0.00816	0.0305	0.0309	-0.0780	-0.0578
			(0.0319)	(0.0319)	(0.0197)	(0.0200)	(0.0200)	(0.0196)	(0.137)	(0.145)
Wheat			0.00251	0.000919	0.0455***	0.0440**	0.0227	0.0225	0.276**	0.299***
			(0.0406)	(0.0408)	(0.0162)	(0.0183)	(0.0175)	(0.0174)	(0.108)	(0.104)
Tobacco+Cane+Rice			0.0248	0.0229	0.0111	0.0101	0.0185	0.0182	0.0195	0.0348
			(0.0690)	(0.0656)	(0.0243)	(0.0226)	(0.0208)	(0.0196)	(0.104)	(0.106)
State FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Ecological controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Distances to water and cities	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Crop-specific controls	N	N	Y	Y	Y	Y	Y	Y	Y	Y
Socio-economic controls	N	N	N	N	N	N	N	N	N	N
Observations	1821	1821	1821	1821	1821	1821	1821	1821	1821	1821
R^2	0.410	0.409	0.438	0.438	0.443	0.443	0.435	0.435	0.447	0.450

Notes: See Appendix A for variable definitions and sources. Robust standard errors clustered at the state level are reported in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

Appendix C. Alternative Measures of Diversity

The degree of diversity in production can be captured by different measures. In the baseline estimates of the paper I consider a commonly used measure of diversity (e.g., Imbs and Wacziarg, 2003; Imbs et al., 2012) and define Agri.Diversity$_c = 1 - \sum_i \theta_{ic}^2$, where θ_{ic} is the share of total agricultural output in county c corresponding to product i (with $i = 1, 2, ..., 36$). In this appendix I check the robustness of the main results (the positive significant impact of early agricultural diversity on contemporary income per capita) to considering alternative measures of diversity.

Most standard measures are constructed as measures of specialization, i.e. higher values represent lower diversity. I consider Krugman's Index of Specialization, which is defined as $\sum_i |\theta_{ic} - \theta_i|$, where θ_i is the share of product i in total agricultural output in the sample; 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, $E(\alpha)_c = \frac{1}{N\alpha(\alpha-1)} \sum_i \left[\left(\theta_{ic}/\bar{\theta}_{ic}\right)^2 - 1 \right]$, 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; the coefficient of variation of product shares, defined as $\sigma_{\theta_{ic}}/\bar{\theta}_{ic}$, where $\sigma_{\theta_{ic}}$ is the standard devation of products shares in county c; and finally, the Gini coefficient of product shares.

Table C1 provides estimates of the effects of agricultural specialization in 1860 as captured by these alternative measures. To facilitate comparison, the first columns report estimates of the effects of agricultural specialization as captured by a Hirschman-Herfindahl index, i.e. one minus the baseline measure of Agri.Diversity$_c$ as defined above. By construction, the estimates are equal to one minus the estimates reported in Table 3. In all cases, the results indicate negative significant effects of agricultural specialization, i.e. positive significant effects of agricultural diversity.

Table C1. Effects of Agricultural Diversity as Captured by Alternative Measures of Specialization

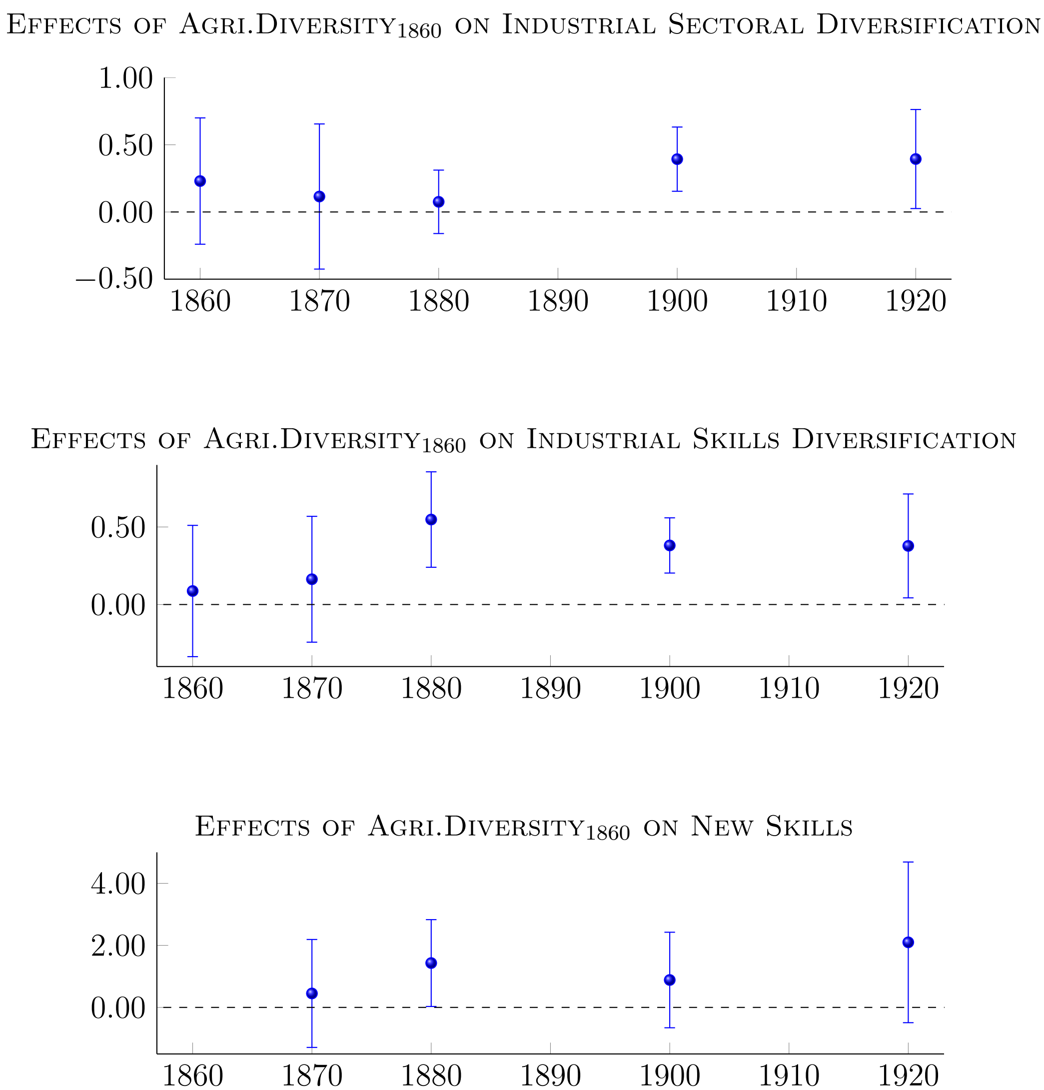
	Dependent variable: Ln Income per capita, 2000											
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Hirschman-Hirfendahl Index	-0.333***	-0.395***										
	(0.0564)	(0.0918)										
Krugman Index			-0.119***	-0.0957*								
			(0.0284)	(0.0558)								
Index of Inequality in Production Structure					-0.237***	-0.228**						
					(0.0626)	(0.110)						
Entropy Index							-0.647***	-0.743***				
							(0.107)	(0.221)				
Coefficient of Variation									-0.383***	-0.417***		
									(0.0582)	(0.129)		
Gini											-0.896***	-0.825*
											(0.176)	(0.440)
State FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Ecological controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Distances to water and cities	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Crop-specific controls	N	N	N	N	N	N	N	N	N	N	N	N
Socio-economic controls	N	N	N	N	N	N	N	N	N	N	N	N
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	0.410	0.409	0.419	0.419	0.421	0.421	0.430	0.429	0.431	0.431	0.421	0.421

Robust standard errors clustered by state in parentheses; * p<0.10, ** p<0.05, *** p<0.01; See pages 11-13 for an explanation of control variables.

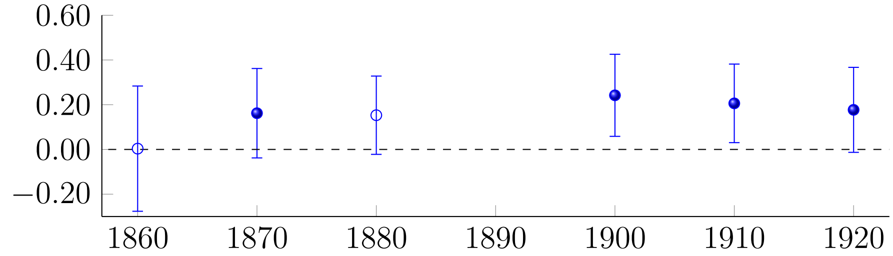
Appendix D. Effects of Agricultural Diversity over Time

Figure D1 displays IV estimates of the effects of agricultural diversity in 1860 on intermediate variables capturing channels through it may have affected development between 1860 and 1920. Overall, the results confirm the patterns established before: the effects of mid-19th century agricultural diversity emerged over the course of the Second Industrial Revolution.

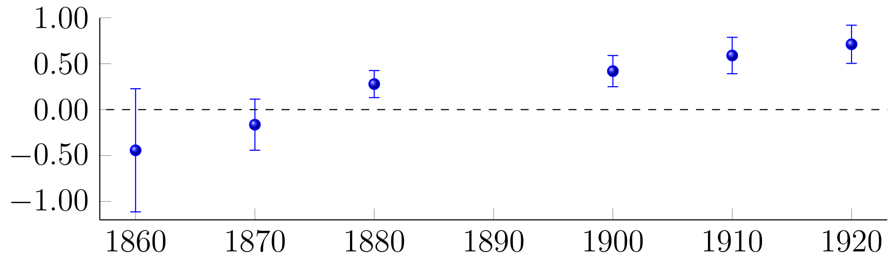
FIGURE D1. EFFECTS OF AGRI.DIVERSITY$_{1860}$ ON INTERMEDIATE VARIABLES (IV ESTIMATES)



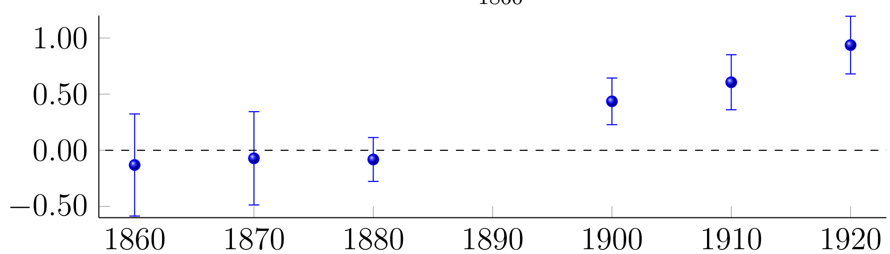
Effects of Agri.Diversity$_{1860}$ on Literacy Rates



Differential Effects of Agri.Diversity$_{1860}$ on Skill-Intensive Sectors



Differential Effects of Agri.Diversity$_{1860}$ on Knowledge-Intensive Sectors

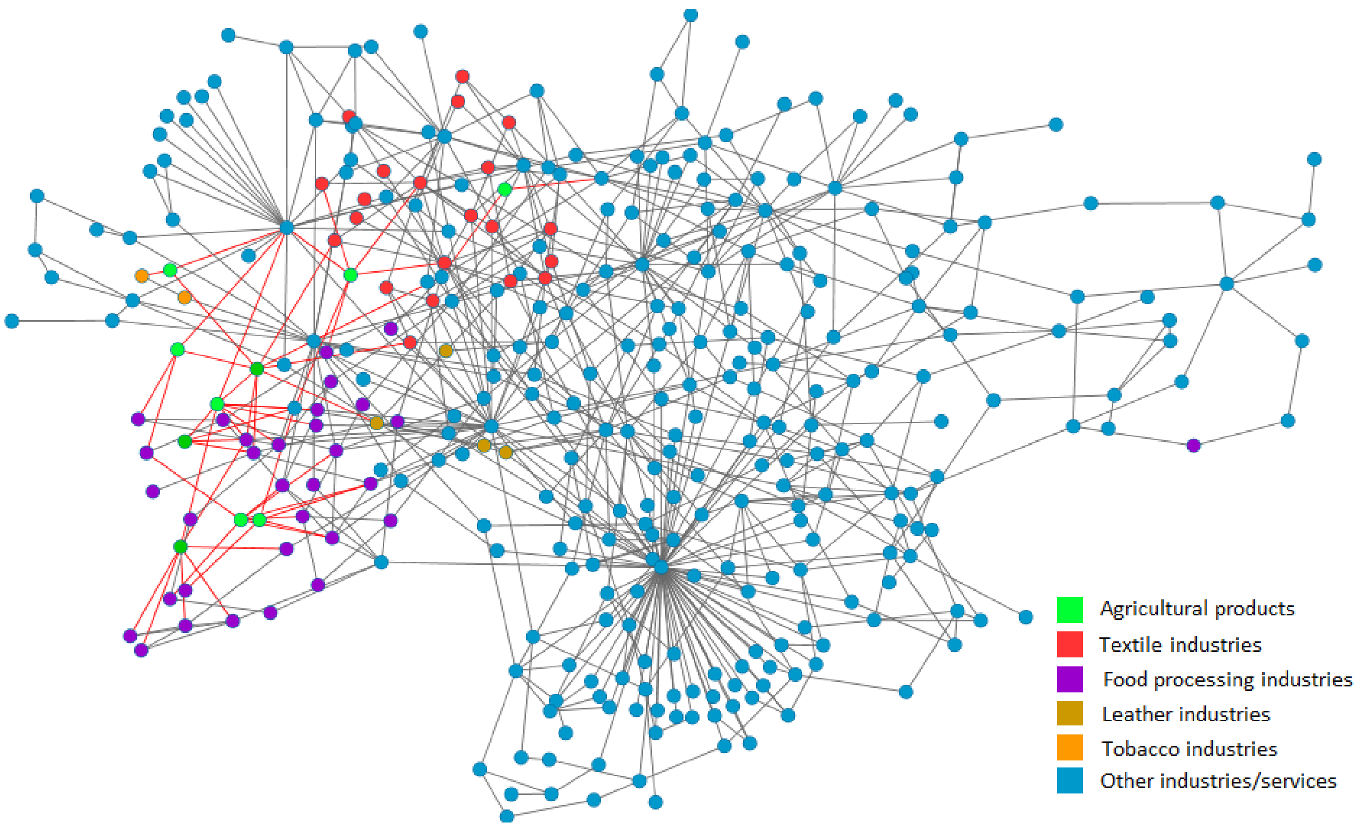


Notes: The graphs display the estimated coefficients on agricultural diversity from regressions for different outcomes variables, controlling for state fixed effects, ecological controls and distances to water and cities. Intervals reflect 95% confidence levels (calculated with robust standard errors clustered at the state-level). See Appendix A for variable definitions and sources. For new skills, literacy rates, agricultural productivity, and farmland share in largest farms, all regressions have 1,821 observations. For industrial sectoral and skill diversification, sample size fluctuates between 1,010 and 1,676 observations; county-industry level observations in cross-county cross-industry regressions have observations for the same number of counties and for 59 industrial sectors.

Appendix E. Input-Ouput Linkages of Agricultural Products

Figure E1 shows the network structure of production based on the input-output table of the US economy in 1963. There are 308 production sectors represented as nodes, and links between pairs of nodes indicate that one of the two sectors represents above 5% of total inputs of the other. The visual arrangement relies on a spring-embedded type of algorithm. Nodes corresponding to agricultural products, textile industries, food-processing industries, leather industries and tobacco industries are displayed in different colors, and the links of agricultural products are displayed in red to bring attention to the key implications of the network representation for the purposes of this paper: various agricultural products provided different "entry points" into the sectoral network of production.

Figure E1. Agricultural Products in the Input-Output Network of Production



Appendix F. Proofs

This appendix contains the proofs of Lemma 1, Lemma 2, and Proposition 3 of the model proposed in Section 6. For convenience, I repeat their statements before presenting the corresponding proofs.

LEMMA 1. Expected efficiency in sector i is increasing in the number of previously existing capabilities in other sectors: $\eta_{E(E_{it}),\Omega_{t-1}^{i'\neq i}} > 0$.

PROOF. Using the definition of $\eta_{E(E_{it}),\Omega_{t-1}^{i'\neq i}}$ and equation (4), we have that

$$\eta_{E(E_{it}),\Omega_{t-1}^{i'\neq i}} = \frac{\left(\frac{1+\Delta\Omega_{t-1}^{i'\neq i}/\Omega_{t-1}^{i'\neq i}}{1+\Delta\Omega_{t-1}^{i'\neq i}/(\Omega_{t-1}^{i'\neq i}+1)}\right)^{J_i} - 1}{\Delta\Omega_{t-1}^{i'\neq i}/\Omega_{t-1}^{i'\neq i}} \quad .$$

Since $\Delta\Omega_{t-1}^{i'\neq i}/(\Omega_{t-1}^{i'\neq i}) > \Delta\Omega_{t-1}^{i'\neq i}/(\Omega_{t-1}^{i'\neq i}+1)$ and $J_i \geq 1$, we have $\left(\frac{1+\Delta\Omega_{t-1}^{i'\neq i}/\Omega_{t-1}^{i'\neq i}}{1+\Delta\Omega_{t-1}^{i'\neq i}/(\Omega_{t-1}^{i'\neq i}+1)}\right)^{J_i} > 1$, and thus $\eta_{E(E_{it}),\Omega_{t-1}^{i'\neq i}} > 0$. □

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

PROOF. Using from the expression for $\eta_{E(E_{it}),\Omega_{t-1}^{i'\neq i}}$ from the proof of Lemma 1, we have that

$$\frac{\Delta\eta_{E(E_{it}),\Omega_{t-1}^{i'\neq i}}}{\Delta J_i} = \frac{\left(\frac{1+\Delta\Omega_{t-1}^{i'\neq i}/\Omega_{t-1}^{i'\neq i}}{1+\Delta\Omega_{t-1}^{i'\neq i}/(\Omega_{t-1}^{i'\neq i}+1)}\right)^{J_i+\Delta J_i} - \left(\frac{1+\Delta\Omega_{t-1}^{i'\neq i}/\Omega_{t-1}^{i'\neq i}}{1+\Delta\Omega_{t-1}^{i'\neq i}/(\Omega_{t-1}^{i'\neq i}+1)}\right)^{J_i}}{\Delta\Omega_{t-1}^{i'\neq i}/\Omega_{t-1}^{i'\neq i}} \quad .$$

Again noting that $\Delta\Omega_{t-1}^{i'\neq i}/(\Omega_{t-1}^{i'\neq i}) > \Delta\Omega_{t-1}^{i'\neq i}/(\Omega_{t-1}^{i'\neq i}+1)$ and $J_i \geq 1$, and also $\Delta J_i \geq 1$, we have that $\left(\frac{1+\Delta\Omega_{t-1}^{i'\neq i}/\Omega_{t-1}^{i'\neq i}}{1+\Delta\Omega_{t-1}^{i'\neq i}/(\Omega_{t-1}^{i'\neq i}+1)}\right)^{J_i+\Delta J_i} > \left(\frac{1+\Delta\Omega_{t-1}^{i'\neq i}/\Omega_{t-1}^{i'\neq i}}{1+\Delta\Omega_{t-1}^{i'\neq i}/(\Omega_{t-1}^{i'\neq i}+1)}\right)^{J_i}$, and thus $\frac{\Delta\eta_{E(E_{it}),\Omega_{t-1}^{i'\neq i}}}{\Delta J_i} > 0$. □

PROPOSITION 3. (*Industrialization*). (a) The number of active industrial sectors is increasing in the number of previously existing operations: $\Delta\sum_{i=1}^{I}\mathbb{1}_{\left[\Omega_{t-1}^{i'\neq i}>\widetilde{\Omega}_i\right]}/\Delta\Omega_{t-1} \geq 0$; (b) The expected value of total industrial employment is non-decreasing in the number of previously existing operations: $\frac{\Delta E\left(\sum_{i=1}^{I} L_{it}\right)}{\Delta\Omega_{t-1}} \geq 0$.

PROOF. (a) Note first that $\Delta\left(\sum_{i=1}^{I} \mathbb{1}_{\left[\Omega_{t-1}^{i'\neq i}>\widetilde{\Omega}_i\right]}\right)/\Delta\Omega_{t-1} = \sum_{i=1}^{I}\left(\Delta\mathbb{1}_{\left[\Omega_{t-1}^{i'\neq i}>\widetilde{\Omega}_i\right]}/\Delta\Omega_{t-1}\right)$. Given that expected employment in each sector depends on capabilities established in *other* sectors, the sectors that account for the change $\Delta\Omega_{t-1}$ need to be specified. For simplicity, assume that the change in established capabilities under consideration corresponds to a single sector, k.[32] In this case, we have that $\Delta\Omega_{t-1}^{i'\neq i} = \Delta\Omega_{t-1}$ for all $i \neq k$ and $\Delta\Omega_{t-1}^{i'\neq k} = 0$, and thus $\Delta\left(\sum_{i=1}^{I} \mathbb{1}_{\left[\Omega_{t-1}^{i'\neq i}>\widetilde{\Omega}_i\right]}\right)/\Delta\Omega_{t-1} = \sum_{i\neq k}\left(\Delta\mathbb{1}_{\left[\Omega_{t-1}^{i'\neq i}>\widetilde{\Omega}_i\right]}/\Delta\Omega_{t-1}^{i'\neq i}\right)$. Next, note that for any $i\neq k$ we have $\Delta\mathbb{1}_{\left[\Omega_{t-1}^{i'\neq i}>\widetilde{\Omega}_i\right]}/\Delta\Omega_{t-1}^{i'\neq i} = \left(\mathbb{1}_{\left[\Omega_{t-1}^{i'\neq i}+\Delta\Omega_{t-1}^{i'\neq i}>\widetilde{\Omega}_i\right]} - \mathbb{1}_{\left[\Omega_{t-1}^{i'\neq i}>\widetilde{\Omega}_i\right]}\right)/\Delta\Omega_{t-1}^{i'\neq i} \geq 0$, because $\mathbb{1}_{\left[\Omega_{t-1}^{i'\neq i}+\Delta\Omega_{t-1}^{i'\neq i}>\widetilde{\Omega}_i\right]} \geq \mathbb{1}_{\left[\Omega_{t-1}^{i'\neq i}>\widetilde{\Omega}_i\right]}$. Thus, $\Delta\left(\sum_{i=1}^{I} \mathbb{1}_{\left[\Omega_{t-1}^{i'\neq i}>\widetilde{\Omega}_i\right]}\right)/\Delta\Omega_{t-1} \geq 0$. □

(b) The proof is similar to that for part (a). Note first that $\frac{\Delta E\left(\sum_{i=1}^{I} L_{it}\right)}{\Delta\Omega_{t-1}} = \sum_{i=1}^{I}\frac{\Delta E(L_{it})}{\Delta\Omega_{t-1}}$. Given that expected employment in each sector depends on capabilities established in *other* sectors, the sectors that account for the change $\Delta\Omega_{t-1}$ need to be specified. For simplicity, assume that the change in established capabilities under consideration corresponds to a single sector, k.[33] In this case, we have that $\Delta\Omega_{t-1}^{i'\neq i} = \Delta\Omega_{t-1}$ for all $i \neq k$ and $\Delta\Omega_{t-1}^{i'\neq k} = 0$, and thus $\frac{\Delta E\left(\sum_{i=1}^{I} L_{it}\right)}{\Delta\Omega_{t-1}} = \sum_{i\neq k}\frac{\Delta E(L_{it})}{\Delta\Omega_{t-1}^{i'\neq i}}$. Recalling that $E(L_{i,t}) = E(L_{i,t}^{*}) \times \mathbb{1}_{\left[\Omega_{t-1}^{i'\neq i}>\widetilde{\Omega}_i\right]}$, note that

$$\frac{\Delta E(L_{it})}{\Delta\Omega_{t-1}^{i'\neq i}} = \frac{\Delta\left(E(L_{i,t}^{*})\times\mathbb{1}_{\left[\Omega_{t-1}^{i'\neq i}>\widetilde{\Omega}_i\right]}\right)}{\Delta\Omega_{t-1}^{i'\neq i}} = \frac{\Delta\left(\left(E(L_{i,t}^{*})+\Delta E(L_{i,t}^{*})\right)\times\mathbb{1}_{\left[\Omega_{t-1}^{i'\neq i}+\Delta\Omega_{t-1}^{i'\neq i}>\widetilde{\Omega}_i\right]} - E(L_{i,t}^{*})\times\mathbb{1}_{\left[\Omega_{t-1}^{i'\neq i}>\widetilde{\Omega}_i\right]}\right)}{\Delta\Omega_{t-1}^{i'\neq i}} \geq 0$$

for any $i\neq k$, because $E(L_{i,t}^{*})+\Delta E(L_{i,t}^{*}) \geq E(L_{i,t}^{*})$ and $\mathbb{1}_{\left[\Omega_{t-1}^{i'\neq i}+\Delta\Omega_{t-1}^{i'\neq i}>\widetilde{\Omega}_i\right]} \geq \mathbb{1}_{\left[\Omega_{t-1}^{i'\neq i}>\widetilde{\Omega}_i\right]}$. Thus, $\frac{\Delta E\left(\sum_{i=1}^{I} L_{it}\right)}{\Delta\Omega_{t-1}} \geq 0$. □

[32]The results can be straightforwardly generalized to a change in established capabilites corresponding to multiple sectors, since such a change can be considered as a sequence of changes corresponding to single sectors.

[33]Idem previous footnote.

References

Acemoglu, D., Johnson, S. and Robinson, A. (2001). The Colonial Origins of Comparative Development: An Empirical Investigation, *The American Economic Review* **91**(5): 1369–1401.

Acemoglu, D. and Zilibotti, F. (1997). Was Prometheus unbound by chance? Risk, diversification, and growth, *Journal of political economy* **105**(4): 709–751.

Adamopoulos, T. (2008). Land inequality and the transition to modern growth, *Review of Economic Dynamics* **11**(2): 257–282.

Akcigit, U., Kerr, W. R. and Nicholas, T. (2013). The Mechanics of Endogenous Innovation and Growth: Evidence from Historical US Patents.

Alvarez-Cuadrado, F. and Poschke, M. (2011). Structural change out of agriculture: Labor push versus labor pull, *American Economic Journal: Macroeconomics* pp. 127–158.

Angrist, J. D. and Pischke, J.-S. (2008). *Mostly harmless econometrics: An empiricist's companion*, Princeton University Press.

Atack, J. and Bateman, F. (1987). *To their own soil: agriculture in the antebellum North*, Ames: Iowa State University Press.

Beaudry, C. and Schiffauerova, A. (2009). Who's right, Marshall or Jacobs? The localization versus urbanization debate, *Research Policy* **38**(2): 318–337.

Berliant, M. and Fujita, M. (2008). Knowledge Creation as a Square Dance on the Hilbert Cube, *International Economic Review* pp. 1251–1295.

Berliant, M. and Fujita, M. (2011). The dynamics of knowledge diversity and economic growth, *Southern Economic Journal* **77**(4): 856–884.

Bleakley, H. and Lin, J. (2012). Portage and path dependence, *The Quarterly Journal of Economics* **127**(2): 587–644.

Bond, S. R. (2002). Dynamic panel data models: a guide to micro data methods and practice, *Portuguese Economic Journal* **1**(2): 141–162.

Bruhn, M. and Gallego, F. A. (2012). Good, bad, and ugly colonial activities: do they matter for economic development?, *Review of Economics and Statistics* **94**(2): 433–461.

Chakraborty, S. and Ray, T. (2007). The development and structure of financial systems, *Journal of Economic Dynamics and Control* **31**(9): 2920–2956.

Chavas, J.-P. and Aliber, M. (1993). An analysis of economic efficiency in agriculture: a nonparametric approach, *Journal of Agricultural and Resource Economics* pp. 1–16.

Cohen, W. M. and Levinthal, D. A. (1990). Absorptive capacity: a new perspective on learning and innovation, *Administrative science quarterly* pp. 128–152.

Combes, P.-P. (2000). Economic structure and local growth: France, 1984–1993, *Journal of urban economics* **47**(3): 329–355.

Combes, P.-P., Duranton, G. and Gobillon, L. (2011). The identification of agglomeration economies, *Journal of economic geography* **11**(2): 253–266.

Conley, T. G. (1999). GMM estimation with cross sectional dependence, *Journal of econometrics* **92**(1): 1–45.

Craig, L. A. (1993). *To sow one acre more: childbearing and farm productivity in the antebellum north*, Johns Hopkins University Press.

Cronon, W. (2009). *Nature's metropolis: Chicago and the Great West*, WW Norton & Company.

Cuadrado-Roura, J. R., García-Greciano, B. and Raymond, J. L. (1999). Regional convergence in productivity and productive structure: The Spanish case, *International Regional Science Review* **22**(1): 35–53.

Desrochers, P. (2001). Local diversity, human creativity, and technological innovation, *Growth and change* **32**(3): 369–394.

Diamond, J. M. (1997). Guns, germs, and steel: The fates of human societies.

Donaldson, D. and Hornbeck, R. (2012). Railroads and American Economic Growth: A Market Access Approach, *Technical report*, National Bureau of Economic Research.

Dornbusch, R., Fischer, S. and Samuelson, P. A. (1977). Comparative advantage, trade, and payments in a Ricardian model with a continuum of goods, *The American Economic Review* **67**(5): 823–839.

Durante, R. (2009). Risk, cooperation and the economic origins of social trust: an empirical investigation.

Duranton, G. and Puga, D. (2001). Nursery cities: Urban diversity, process innovation, and the life cycle of products, *American Economic Review* pp. 1454–1477.

Earle, C. and Hoffman, R. (1980). The Foundation of the Modern Economy: Agriculture and the Costs of Labor in the United States and England, 1800-60, *The American Historical Review* **85**(5): 1055–1094.

Eaton, J. and Kortum, S. (2002). Technology, geography, and trade, *Econometrica* **70**(5): 1741–1779.

Ellison, G., Glaeser, E. L. and Kerr, W. R. (2010). What Causes Industry Agglomeration? Evidence from Coagglomeration Patterns, *American Economic Review* **100**: 1195–1213.

Engerman, S. L. and Sokoloff, K. L. (2002). Factor Endowments, Inequality, and Paths of Development Among New World Economics, *Technical report*, National Bureau of Economic Research, Inc.

Engerman, S. and Sokoloff, K. (1997). Factor Endowments, Institutions, and Differential Paths of Growth Among New World Economies, *How Latin America Fell Behind: Essays on the Economic Histories of Brazil and Mexico, 1800-1914* **89**: 260.

Erb, K.-H., Gaube, V., Krausmann, F., Plutzar, C., Bondeau, A. and Haberl, H. (2007). A comprehensive global 5min resolution land-use data set for the year 2000 consistent with national census data, *Journal of Land Use Science* **2**(3): 191–224.

Fenske, J. (2014). Ecology, Trade, and States in Pre-Colonial Africa, *Journal of the European Economic Association* **12**(3): 612–640.

Galiani, S., Heymann, D., Dabus, C. and Tohmé, F. (2008). On the emergence of public education in land-rich economies, *Journal of Development Economics* **86**(2): 434–446.

Galor, O. (2011). *Unified growth theory*, Princeton University Press.

Galor, O., Moav, O. and Vollrath, D. (2009). Inequality in Landownership, the Emergence of Human-Capital Promoting Institutions, and the Great Divergence, *The Review of Economic Studies* **76**(1): 143–179.

Glaeser, E. L., Kallal, H. D., Scheinkman, J. A. and Shleifer, A. (1992). Growth in Cities, *Journal of Political Economy* **100**(6).

Glaeser, E. L., Kerr, S. P. and Kerr, W. R. (2012). Entrepreneurship and urban growth: An empirical assessment with historical mines, *Technical report*, National Bureau of Economic Research.

Goldin, C. and Sokoloff, K. (1984). The relative productivity hypothesis of industrialization: The American case, 1820 to 1850, *The Quarterly Journal of Economics* **99**(3): 461–487.

Gollin, D., Parente, S. and Rogerson, R. (2002). The role of agriculture in development, *The American Economic Review* **92**(2): 160–164.

Greene, W. (2010). Testing hypotheses about interaction terms in nonlinear models, *Economics Letters* **107**(2): 291–296.

Haines, M. R. and ICPSR (2010). *Historical, Demographic, Economic, and Social Data: The United States, 1790-2002*, Interuniversity Consortium for Political and Social Research.

Harris, C. D. (1954). The Market as a Factor in the Localization of Industry in the United States, *Annals of the association of American geographers* **44**(4): 315–348.

Hausmann, R. and Hidalgo, C. A. (2011). The network structure of economic output, *Journal of Economic Growth* **16**(4): 309–342.

Helsley, R. W. and Strange, W. C. (2002). Innovation and input sharing, *Journal of Urban Economics* **51**(1): 25–45.

Henderson, V., Kuncoro, A. and Turner, M. (1995). Industrial Development in Cities, *Journal of Political Economy* pp. 1067–1090.

Herrendorf, B., Rogerson, R. and Valentinyi, A. (2013). Growth and Structural Transformation, *Technical report*, National Bureau of Economic Research.

Hirschman, A. O. (1981). Essays in trespassing, *Cambridge Books* .

Hornbeck, R. (2012). The Enduring Impact of the American Dust Bowl: Short-and Long-Run Adjustments to Environmental Catastrophe, *American Economic Review* **102**(4): 1477–1507.

Hounshell, D. (1985). *From the American system to mass production, 1800-1932: The development of manufacturing technology in the United States*, JHU Press.

Imbs, J., Montenegro, C. and Wacziarg, R. (2012). Economic Integration and Structural Change, *mimeo* .

Imbs, J. and Wacziarg, R. (2003). Stages of diversification, *American Economic Review* pp. 63–86.

Jacobs, J. (1969). *The economies of cities*, Random House.

Johnston, B. F. and Mellor, J. W. (1961). The role of agriculture in economic development, *The*

American Economic Review pp. 566–593.

Jones, C. I. (2011). Intermediate goods and weak links in the theory of economic development, *American Economic Journal: Macroeconomics* pp. 1–28.

Kim, K., Chavas, J.-P., Barham, B. and Foltz, J. (2012). Specialization, diversification, and productivity: a panel data analysis of rice farms in korea, *Agricultural Economics* **43**(6): 687–700.

Kleibergen, F. and Paap, R. (2006). Generalized reduced rank tests using the singular value decomposition, *Journal of Econometrics* **133**(1): 97–126.

Koren, M. and Tenreyro, S. (2013). Technological diversification, *The American Economic Review* **103**(1): 378–414.

Kremer, M. (1993). The O-ring theory of economic development, *The Quarterly Journal of Economics* pp. 551–575.

Krugman, P. (1991). Increasing Returns and Economic Geography, *The Journal of Political Economy* **99**(3): 483–499.

Marshall, A. (1895). *Principles of Economics*, The English Langugage Book Society; London.

Matsuyama, K. (1992). Agricultural productivity, comparative advantage, and economic growth, *Journal of economic theory* **58**(2): 317–334.

McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior, *in P. Zarembka, Frontiers in econometrics* pp. 105–142.

Meyer, D. R. (1989). Midwestern industrialization and the American manufacturing belt in the nineteenth century, *The Journal of Economic History* **49**(04): 921–937.

Michalopoulos, S. (2012). The Origins of Ethnolinguistic Diversity, *American Economic Review* **102**(4): 1508–39.

Mullahy, J. (2011). Multivariate fractional regression estimation of econometric share models, *Journal of Econometric Methods* .

Nunn, N. (2008). Slavery, Inequality, and Economic Development in the Americas, *Institutions and economic performance* .

Nunn, N. (2013). Historical Development, *The Handbook of Economic Growth* **2**.

Olmstead, A. L. and Rhode, P. W. (2009). Conceptual issues for the comparative study of agricultural development, in Agriculture and Economic Development in Europe since 1870, edited by Pedro Lains and Vicente Pinilla.

Page, B. and Walker, R. (1991). From settlement to Fordism: the agro-industrial revolution in the American Midwest, *Economic Geography* pp. 281–315.

Papke, L. E. and Wooldridge, J. M. (1996). Econometric Methods for Fractional Response Variables With an Application to 401 (K) Plan Participation Rates, *Journal of Applied Econometrics* pp. 619–632.

Paul, C. J. M. and Nehring, R. (2005). Product diversification, production systems, and economic performance in U.S. agricultural production, *Journal of Econometrics* **126**(2): 525 – 548. Current developments in productivity and efficiency measurement.

Pudup, M. B. (1987). From farm to factory: structuring and location of the US farm machinery industry, *Economic Geography* pp. 203–222.

Rajan, R. G. and Ramcharan, R. (2011). Land and credit: A study of the political economy of banking in the united states in the early 20th century, *The journal of finance* **66**(6): 1895–1931.

Rajan, R. G. and Zingales, L. (1998). Financial Dependence and Growth, *American Economic Review* pp. 559–586.

Ramalho, E. A., Ramalho, J. J. and Murteira, J. M. (2011). Alternative estimating and testing empirical strategies for fractional regression models, *Journal of Economic Surveys* **25**(1): 19–68.

Ramankutty, N., Foley, J. A., Norman, J. and McSweeney, K. (2002). The global distribution of cultivable lands: current patterns and sensitivity to possible climate change, *Global Ecology and Biogeography* **11**(5): 377–392.

Ramcharan, R. (2010a). Inequality and redistribution: Evidence from US counties and states, 1890-1930, *The Review of Economics and Statistics* **92**(4): 729–744.

Ramcharan, R. (2010b). The link between the economic structure and financial development, *The BE Journal of Macroeconomics* **10**(1).

Rhode, P. W. and Strumpf, K. S. (2003). Assessing the importance of Tiebout sorting: Local heterogeneity from 1850 to 1990, *The American Economic Review* **93**(5): 1648–1677.

Romer, P. M. (1990). Endogenous Technological Change, *Journal of Political Economy* pp. S71–S102.

Rosenberg, N. (1979). Technological interdependence in the American economy, *Technology and Culture* pp. 25–50.

Ruggles, S., Alexander, J. T., Genadek, K., Goeken, R., Schroeder, M. B. and Sobek, M. (2010). *Integrated Public Use Microdata Series: Version 5.0*, University of Minnesota.

Russelle, M. P., Entz, M. H. and Franzluebbers, A. J. (2007). Reconsidering integrated crop–livestock systems in North America, *Agronomy Journal* **99**(2): 325–334.

Scherer, F. M. (1982). Inter-industry technology flows and productivity growth, *The review of economics and statistics* pp. 627–634.

Schmookler, J. (1966). Invention and economic growth.

Schumpeter, J. A. (1934). *The theory of economic development: An inquiry into profits, capital, credit, interest, and the business cycle*, Vol. 55, Transaction Publishers.

Sivakumar, A. and Bhat, C. (2002). Fractional split-distribution model for statewide commodity-flow analysis, *Transportation Research Record: Journal of the Transportation Research Board* **1790**(1): 80–88.

Sokoloff, K. L. and Dollar, D. (1997). Agricultural Seasonalily and the Organization of Manufacturing in Early Industrial Economies: The Contrast Between England and the United States, *The Journal of Economic History* **57**(02): 288–321.

Spolaore, E. and Wacziarg, R. (2013). How Deep Are the Roots of Economic Development?, *Journal of Economic Literature* **51**: 325–69.

Usher, A. P. (1929). *A History of Mechanical Inventions*, McGraw-Hill, New York and London.

Van den Bergh, J. C. (2008). Optimal diversity: increasing returns versus recombinant innovation, *Journal of Economic Behavior & Organization* **68**(3): 565–580.

Vollrath, D. (2013). Inequality and school funding in the rural United States, 1890, *Explorations in Economic History* **50**(2): 267–284.

Weiss, T. J. (1992). US Labor Force Estimates and Economic Growth, 1800-1860, *American economic growth and standards of living before the Civil War*, University of Chicago Press, pp. 19–78.

Weitzman, M. L. (1998). Recombinant growth, *Quarterly Journal of Economics* pp. 331–360.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*, MIT press.

Zeppini, P. and Van den Bergh, J. C. (2013). Optimal diversity in investments with recombinant innovation, *Structural Change and Economic Dynamics* **24**: 141–156.