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

Martin Fiszbein†

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Abstract

This paper examines the role of agricultural diversity in the process of economic development. Evidence from U.S. counties shows that early agricultural diversification affected structural change and long-run economic performance. Using a novel identification strategy that relies on exogenous variation in patterns of agricultural production generated by climatic features, I find sizable effects of agricultural diversification in the mid-19th century on income per capita in recent decades. A positive impact of agricultural diversity can be traced back to the advance of the industrialization process in the course of the Second Industrial Revolution. An assessment of mechanisms suggests that agricultural diversity boosted the relative size and productivity of the manufacturing sector by fostering manufacturing diversification (in terms of sectors and skills), formation of new skills, and technological progress. (*JEL* O11, O41, N11, N51)

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

1 Introduction

In search for explanations of income disparities observed across the world, researchers have directed their attention to the transformations of agricultural economies into modern industrial economies (Galor and Weil, 2000; Lucas, 2000; Hansen and Prescott, 2002). In turn, the timing and depth of transitions into modern economic growth depend on the characteristics of pre-industrial societies. The importance of history for comparative economic development is highlighted by a burgeoning literature that uncovers the persistent effects of deeply-rooted factors (see Galor, 2011; Nunn, 2013; Spolaore and Wacziarg, 2013).

Among deep-rooted determinants of long-run growth, this paper focuses on patterns of production at early stages of development. The impact of agricultural productivity and land abundance have attracted considerable attention in the literature on economic development (Matsuyama, 1992; Gollin et al., 2002; Galiani et al., 2008). The effects of particular specialization patterns have also been extensively studied (Engerman and Sokoloff, 1997, 2002; Bruhn and Gallego, 2012). In contrast, the role of agricultural diversity remains largely unexplored.[3]

Why would agricultural diversity matter for economic development? On the one hand, diversification may imply foregoing increasing returns to scale or knowledge spillovers that operate only within a sector. On the other hand, under complementarities between inputs or skills, diversity can increase productivity; moreover, a diverse economic environment may foster skill formation and technological dynamism. While this channel plays the leading role in the context of this paper, other mechanisms are also considered. Positive effects of diversificaty could also arise from increased agricultural productivity, or from lower risk exposure and reduced volatility. In addition, diversity may be associated with lower inequality in land ownership, which may in turn affect local financial and educational institutions.

I use a rich dataset of U.S. counties spanning 140 years to study the effects of agricultural diversity on long-run development. The empirical analysis shows a robust positive relationship between early agricultural diversification (in 1860) and recent measures of development (such as per capita income in 2000). Rather than reflecting an immediate effect, the relationship between diversity and income emerged over the course of the development process. I show that agricultural diversification in the mid-19th century is positively asso-

[3]To my knowledge, the only 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.

ciated with the share of population employed in manufacturing towards the 20th century, but not before. This suggests that diversity affected patterns of structural change over the course of the Second Industrial Revolution, a key historical period (usually dated 1870-1920) in which the US was transformed from a predominantly agricultural economy into the leading industrial producer in the world.

The positive correlation 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 environmental conditions, distances to major urban centers and waterways, and an extensive set of socio-economic variables. Controlling for state fixed effects allows 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). To identify the causal effects of agricultural diversity, I propose an instrumental variable (IV) strategy that exploits exogenous variation in agricultural production patterns generated by natural endowments.

The identification strategy relies on an IV for agricultural diversity that I construct using measures of potential productivity for different crops based on climate data. I estimate a fractional multinomial logit model of crop choice in which the outcome variables are the shares of each agricultural product in total agricultural output at the county-level, and the crop-specific climate-based 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 two-stage least squares (2SLS) estimates of the effects of agricultural diversity on development outcomes.

After establishing that early agricultural diversification had long-term positive effects, I proceed to examine the channel. Highlighting the role of cross-sectoral spillovers, complementarities, and recombinations, I show evidence suggesting that the positive impact of agricultural diversity operated through higher manufacturing productivity, increased variety of industrial products and skills, accelerated acquisition of novel productive capabilities and enhanced technological dynamism. The relevance of this set of mechanisms is demonstrated by the positive effects on key intermediate variables –sectoral and skills diversity in manufacturing, counts of novel productive capabilities, and patent activity– at the peak of the Second Industrial Revolution. Furthermore, cross-county cross-industry regressions show that agricultural diversity had a positive differential impact on skill-intensive and knowledge-intensive industrial sectors, lending further support to the hypothesis that early diversification spurred growth by fostering the formation of new skills and technological dynamism.

The evidence does not support the relevance of other mechanisms that could explain the long-run impact of early agricultural diversity. There is no evidence that agricultural diversity affected development outcomes through agricultural productivity, which underlines the cross-sectoral nature of the impact of early agricultural diversity on the process of development. Next, I construct a measure of predicted volatility based on the initial composition of agricultural production and the evolution of national prices, which I use to assess whether agricultural diversification boosted economic performance by reducing volatility in the value of agricultural production; the evidence does not support this mechanism. Finally, I assess 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.

The results complement recent quantitave studies of US history showing persistent effects of geographical features that are no longer directly relevant (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, 2002). While highlighting the long-run impact of geographic endowments originated in their influence on agricultural production patterns, my research uncovers the role of diversity beyond the relevance of particular crops. This focus on diversity offers a distinct addition to the extensive literature on the role of agriculture in the process of economic development.

The paper contributes to the literature on diversification and growth (e.g., Acemoglu and Zilibotti, 1997; Imbs and Wacziarg, 2003; Koren and Tenreyro, 2013), providing an analysis of different channels in historical perspective and a focus on the agricultural sector that permits a novel identification strategy. The empirical findings provide strong support for the relevance of set of mechanisms that have attracted considerable attention in the urban economics literature (e.g., Glaeser et al., 1992; Henderson et al., 1995; Combes, 2000). The importance of agricultural 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 cross-sectoral linkages and complementarities in multi-sector 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 diversification and growth. 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. Sections five and six explore the mechanisms through which diversity could have affected productivity in the course of the industrialization process. The final section concludes.

2 Diversity and Development: Theories and Evidence

The relationship between diversification 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 address the relationship between diversity and development for the economy as a whole, are relevant in the context of this paper notwithstanding my focus on *agricultural* diversity. Section 5 elaborates on this at length. For the moment, note that the focus on agricultural diversification is not a narrow one, since in the mid-nineteenth century agriculture was the main sector of the US economy; moreover, through the linkages between different agricultural and industrial products, agricultural diversity may be the root of economy-wide diversification.

Long-standing pieces of conventional 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 clustering together with firms in the same sector. Also prominent among the theoretical underpinnings of arguments for specialization are the concepts of comparative advantage and gains from trade. Standard trade theory posits that increased trade openness or reduced transport costs foster specialization and also increase income. This prediction arises from models in the Hecksher-Ohlin tradition, as well as in Ricardian trade 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.[4] Finally, a cursory consideration of modern portfolio theory might also suggest that diversification hinders growth, insofar as –with the purpose

[4]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.

of attenuating risk– it reduces the expected returns.

In contrast, there are theories that imply a positive relationship between diversity and development. A basic idea suggesting positive effects of diversity is that under imperfect substitutabiilty between inputs (or skills, or technologies), a broader range of productive activities yields efficiency gains. This can be captured, as in endogenous growth models with expanding varieties *à la* Romer (1990) and New Economic Geography models *à la* Krugman (1991), with a CES production function in which the number of input varieties positively affects the level of output – the analogous on the production side to "love-of-variety" in consumption.[5] Jones (2011) offers a discussion of the properties of CES productions functions in connection with the role of linkages and complementarities in development, and proposes a model higlighting how "a chain is only as strong as its weakest link." The same feature was captured in a different setup by Kremer (1993).

This paper favors a view that emphasizes the *dynamic* effects of diversity. Going back to Jacobs (1969), the idea of "Jacobs externalities" –connected with urbanization economies, in particular those operating through increased flows of knowledge– is that diversity can foster technological dynamism, i.e. 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 also at the generation of innovations as recombinations of old ideas (already hinted at by Usher (1929) and Schumpeter (1934)). Rosenberg (1979) emphasizes technological interdepence and provides a number of examples from American economic history that illustrate complementarities between different technologies.

The recombination of existing ideas as the source of new technologies 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 characterizing alternative investment options push allocations toward 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.

While the literature usually emphasizes innovation, the positive impact of diversity

[5]While CES production functions with imperfect substitutability featured in these models are sometimes interpreted as capturing the Smithian idea that the division of labor increases productivity, the implied relationship between the number of input varieties and the level of output is mechanic, and most formulations do not go beyond static effects of variety.

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 entrepreneurs 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, 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 have the possibility of entering 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 diversification and development, the identification of causal effects is challenging, and it is not surprising that empirical studies have not produced conclusive evidence. 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 the evolution of trade in two distinct stages of integration (first between regions and then between countries, with opposite effects on country-level diversification). The effects of diversification have been assessed by a large number of papers in the urban economics literature, but the evidence on the quantitive relevance of localization versus Jacobs externalities is mixed (for a comprehensive review, see Beaudry and Schiffauerova, 2009).

3 Agricultural Diversity and Long-Run Development across US Counties: A First Look

3.1 Data on Agricultural Production and Development Outcomes

Historical data on county-level agricultural and manufacturing production as well as several socio-economic variables come from United States censuses from 1860 to 1940, available from National Historical Geographic Information Systems (NHGIS) (Minnesota Population Center, 2011). Data on personal income and population (used to calculate income per capita) in 1970, 1980, 1990 and 2000 is obtained from the Bureau of Economic Analysis. Data on manufacturing employment, value added, and wages at several points in time from 1940 onwards are obtained from County Data Books compiled by the U.S. Census Bureau and available from Haines et al. (2010). Employment microdata from US censuses is obtained from Ruggles et al. (2010).

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.[6] Most of the empirical analysis is conducted on the sample of 1,821 counties displayed in gray in Figure 1.

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. In any case, 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 a GIS software– I determine the county defined in 1860 that contained each county or county fragment defined in 2000,

[6] 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 1. Continental US counties, 1860

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.

In 1860, over 55% of the labor force was employed in agricultural production, which accounted for around 45% of output in the US economy (Weiss, 1992). Within my sample, the share of the total labor force employed in agriculture was around 60%, and almost 70% of counties had over 90% of their labor force employed in agriculture. To study how patterns of agricultural production in this early stage of development affected subsequent growth paths, I use detailed data on agricultural activities. The 1860 Decennial Census provides data on the value of agricultural output for 36 agricultural products composing agricultural production. Table 1 reports the share of total agricultural production that each of these agricultural products represents in my sample of US counties as well as the maximum percentage share of value that each product attains across these counties, the percentage of counties in which a product was the dominant one and the percentage in which it represented over 50% of agricultural output. As can be seen, even marginal products represent large shares of agricultural output in some counties (e.g., rice, which amounts to less that 0.3% of total agriculural output, had a share larger than 86% in Georgetown, South Carolina).

Table 1. Agricultural Production Data

Product	% of Agr.Output		% of Counties		Product	% of Agr.Output		% of Counties	
	Overall	Max	Dominant	>50%		Overall	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 data from the US Census, 1859/1860. The statistics for the 36 products that comprise agricultural production are for the sample of 1,821 counties considered in this paper. The first column for each product indicates the share of total agricultural production in this sample corresponding to the product; the second column shows the maximum percentage share of value attained by the product in a county within the sample; the third column indicates the percentage of counties in which each product was the dominant one (i.e., in which its share was the largest one); the fourth column shows the percentage of counties in which it represented over 50% of the county's agricultural output.

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 $\text{Agri.Diversity}_c = 1 - \sum_i \theta_{ic}^2$. As can be seen in Figure 2, 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. Besides the regional disparities, diversification shows significant variation within states, which is important for identification of its effects.

Besides personal income per capita in 2000 (which reflects present-day levels of development), a key outcome variable in the empirical analysis is the share of population in the industrial sector in 1900 (which captures the advance of the industrialization process during the Second Industrial Revolution).

Figure 2. Agricultural diversity, 1860

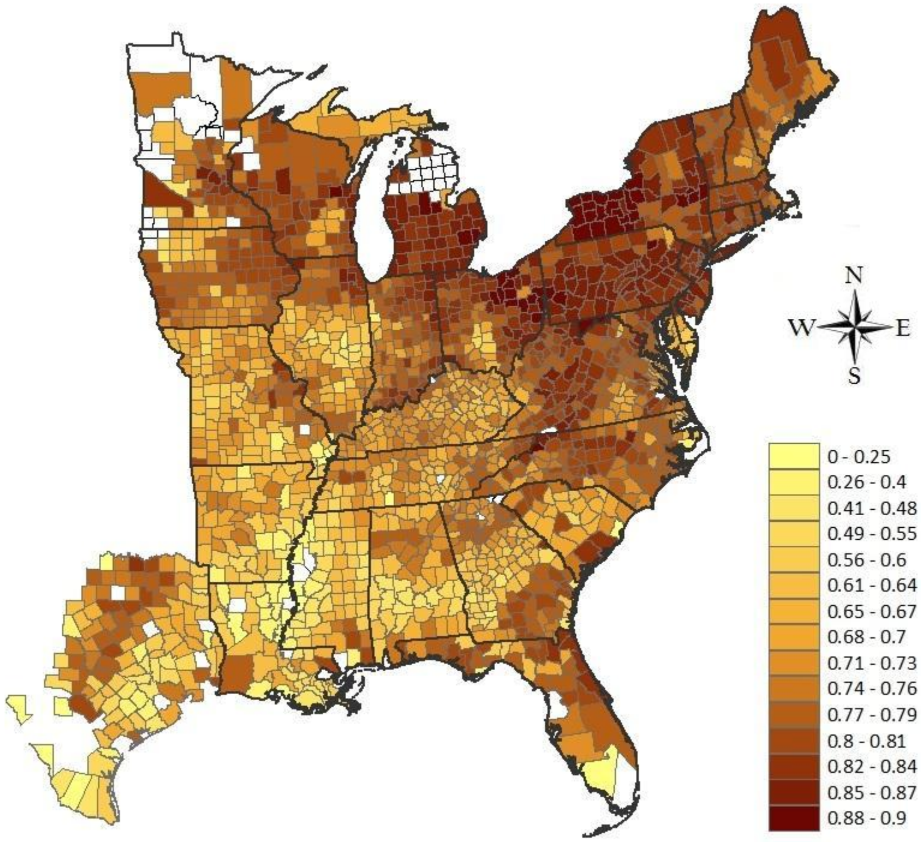


Figure 3 shows the spatial distribution of the share of population in the industrial sector in 1900 and personal income per capita in 2000. Not surprisingly, 1900 levels of industrialization are higher in the North than in the South, but there is also significant variation within states. Figure 3b displays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

3.2 Estimating Equation and OLS Results

This section presents the basic specification and OLS results. To estimate the long-run impact of agricultural diversity, I use the following estimating equation:

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

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. I estimate a series of regressions adding controls sequentially.

Fig.3a. Share of Population in Manufacturing, 1900

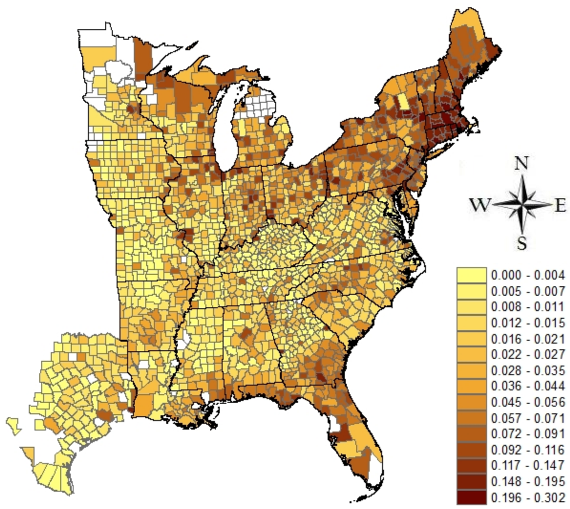
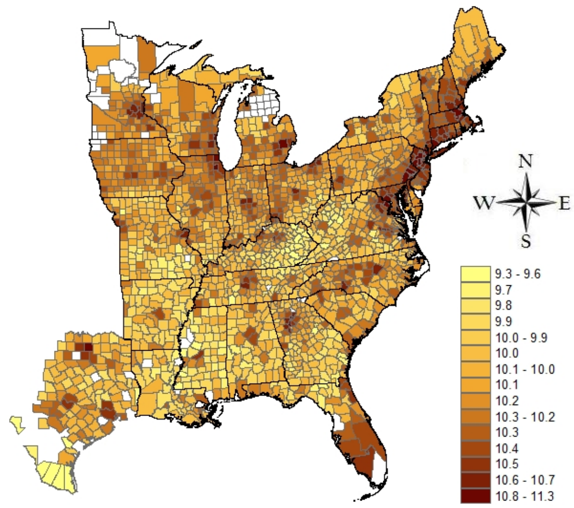


Fig.3b.Ln Income per capita, 2000



The vector of time-invariant controls, $\mathbf{X}_c$, comprises a rich set of variables. First, I control for a host of ecological variables, starting with land productivity measures. I include a measure of overall land suitability as well as productivity measures based on product-specific potential yields (the max and average of attainable yields for the five major products).[7] 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. Besides all the previous ecological controls, I include 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

[7]These data will be discussed in detail in section 4.1. To make yields for different products comparable from an economic viewpoint despite differences in prices and costs of production, each product-specific attainable yield is normalized by the max attained in the sample before computing the max and average.

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 product has the largest share in a county's agricultural production.[8] I also control for the extent of plantation crops (i.e., the combined share of cotton, tobacco, sugarcane, rice), which is emphasized by Engerman and Sokoloff (1997, 2002) to explain the US North-South divide; although this divide is not picked up in 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).[9] 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 $M_{c,1860}$ are predetermined with respect to the outcome

[8]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 A. The results also hold when considering alternative measures of agricultural diversification; see Appendix B.

[9]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 affect the results presented in this paper.

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 6 different specifications of regressions with income per capita in 2000 (Panel 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.[10]

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 4 shows estimates of the coefficient on $\text{Agri.Diversity}_{1860}$ for different outcome variables at different times (with the corresponding 95% confidence intervals) for my preferred specification (i.e., controlling for X_c and Δ_c, but not $M_{c,1860}$). 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. Figure 4 also shows the correlations of early agricultural diversification with two measures of manufacuring productivity, value added per worker and average manufacturing wages (both in logs).[11] Although the pattern is not as clear, the conditional correlations with

[10]The results are qualitatively the same if I control for the (ln 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, for example, Bond, 2002).

[11]Manufacturing labor valued added per worker is the measure of manufacturing labor productivity

early agricultural diversity are in most cases positive and significant as from the early 20th century, but not before.

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***	0.0301**
	(0.0160)	(0.0102)	(0.0099)	(0.0107)	(0.0106)	(0.0114)
R^2	0.087	0.439	0.460	0.480	0.491	0.617
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

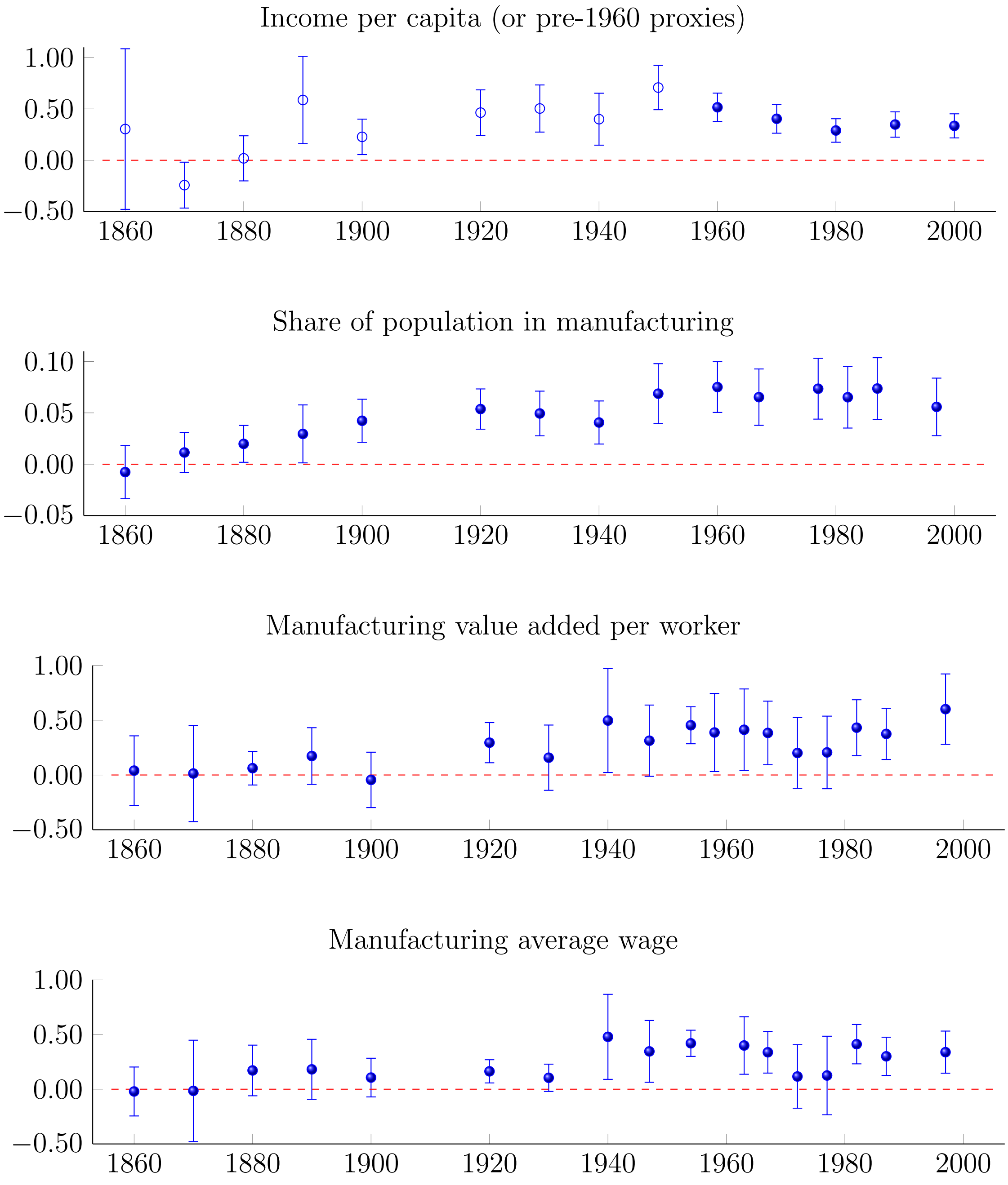
Robust standard errors clustered by state in parentheses

* p<0.10, ** p<0.05, *** p<0.01

See pages 11-12 for an explanation of control variables

used by Atack et al. (2008) in their study of labor productivity growth in nineteenth century American manufacturing.

Figure 4. Agricultural diversity 1860 and development outcomes over time



Notes: The graphs display the estimated coefficients of regressions for different outcomes variables on agricultural diversification 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 ommitted variables that induced higher diversification in 1860 and also improved subsequent economic performance. For example, diversity may reflect high propensity to adopt new ideas and/or higher human capital, which would also boost industrial development.[12] Another possibility 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.[13]

Conversely, 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 also partly reflect a higher level of risk aversion, which could in turn hamper productivity growth in the nascent manufacturing sector. Higher diversification could also reflect the predominance of traditional agriculture –implying that 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.

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 diversification generated by climatic features.

[12]Since agricultural production data was collected for the year as a whole, agricultural diversity reflects to some extent the prevalence of crop rotation (i.e., diversification over time rather than over space). Thus, as an example of the source of bias described above, farmers' education could drive both the adoption of crop rotation schemes and subsequent growth. The instrumental variable approach would take care of this bias.

[13]A positive correlation between diversity in the demand for agricultural products and income levels could arise if some goods (e.g. meat, cheese, fuits) 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.

4.1 Agricultural Productivity Data and IV Construction

The identification strategy proposed here 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 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 also use data on grazing suitability from Erb et al. (2007), who provide a world map with grid cells of 0.083x0.083 degrees classified into four grazing suitability classes.[14] Finally, I use a general measure of land suitability for cultivation –to be interpreted as the probability that each grid cell will be cultivated– constructed by Ramankutty et al. (2002) for grid cells of 0.5x0.5 degrees.

Figure 5 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 highest values in the map of wheat productivities rather than those for corn. Productivity for corn production, which is highest in the Cotton belt, is still high in the Midwest. Thus, as suggested by these broad regional patterns, it is necessary to think in terms of *relative* productivities.

Variation in agricultural diversity generated by variation in relative crop-specific productivities is key for the identification strategy. Intuitively, a county that has similar levels of productivity for several 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 using 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

[14] 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.

an arbitrary number of choices, and can be applied to the context under consideration in a straightforward way, 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 A_c.[15] The functional form considered is the following

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

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

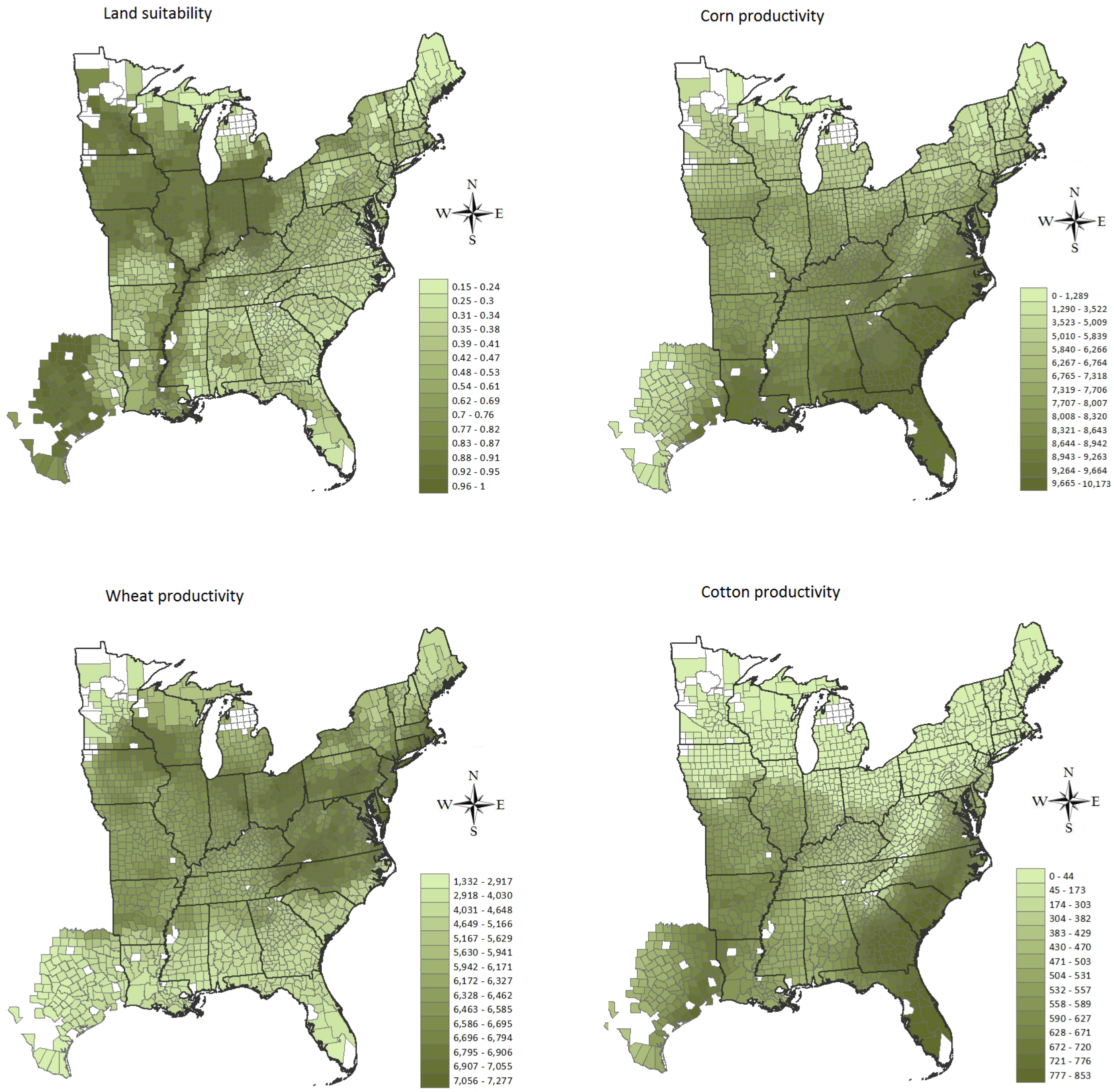
This general setup and this particular functional form can be derived from a simple optimal crop choice model under some assumptions. Reinterpreting the conditional logit framework of choice behavior due to McFadden (1974) in terms of profit maximization rather than utility maximization, assume that profits obtained when choosing crop i for a unit of farm resources j are $\pi_{ij} = \beta_i' A_j + \mu_{ij}$. The relative magnitudes of the β_i's reflect, among other things, the price (and cost) differentials among agricultural products, which farmers take as given. 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 $\frac{e^{\beta_i' A_j}}{1+\sum_{j=1}^{I-1} e^{\beta_j' A_j}}$.

Thus, we get exactly the same functional form to describe the expected shares farm resources used for of each agricultural product as a function of the vector of crop-specific productivities. Assuming that revenues are proportional to farm resources used in each product (or simply that deviations from this are random), the expected shares of each product in total agricultural output at the county level correspond exactly to the equations specified in the multinomial fractional logit model.

Figure 6 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

[15] 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, which should help to predict the shares of the products for which there is no productivity data available.

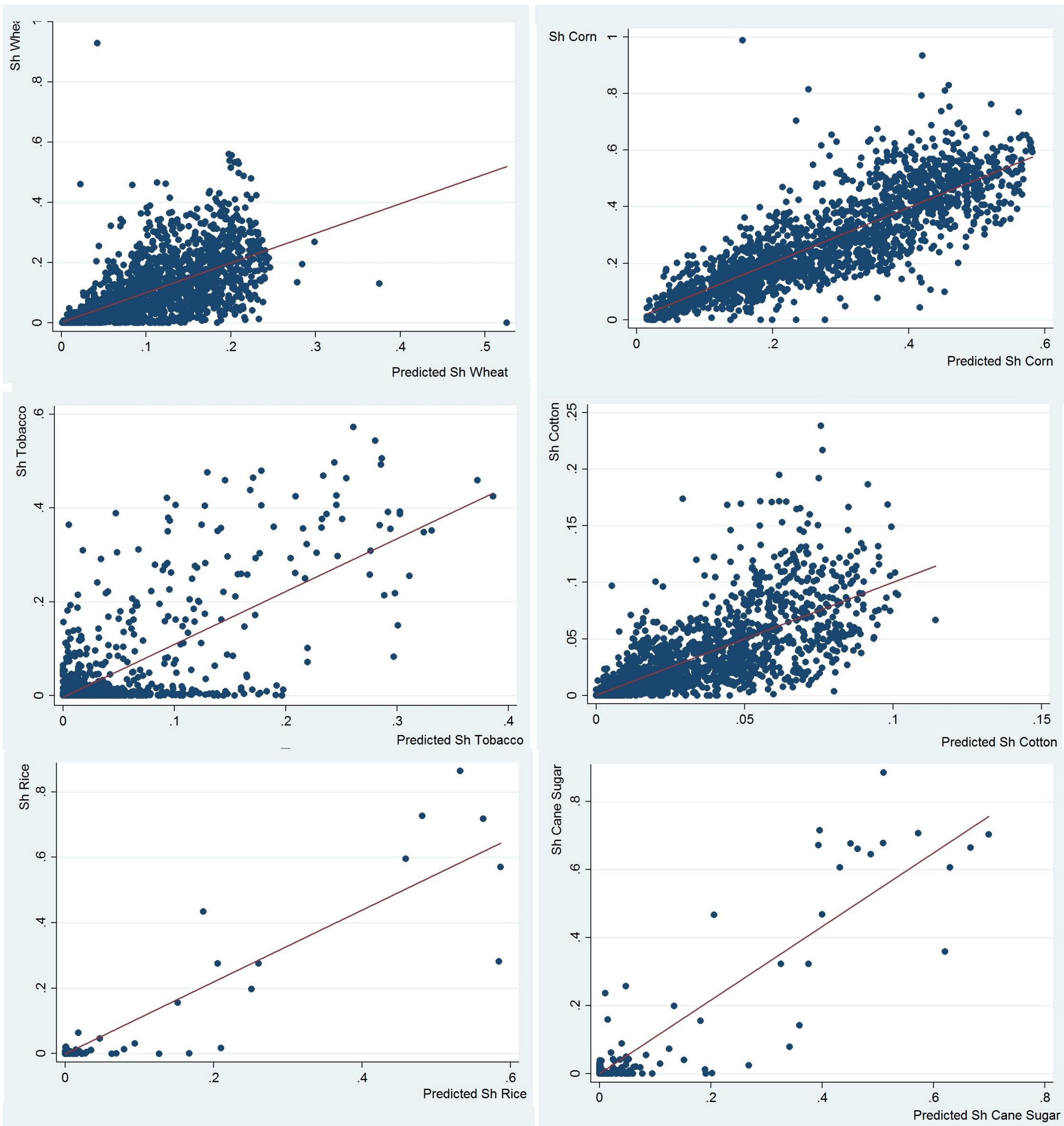
Figure 5. Land suitability and selected crop-specific productivities



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.

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 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 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

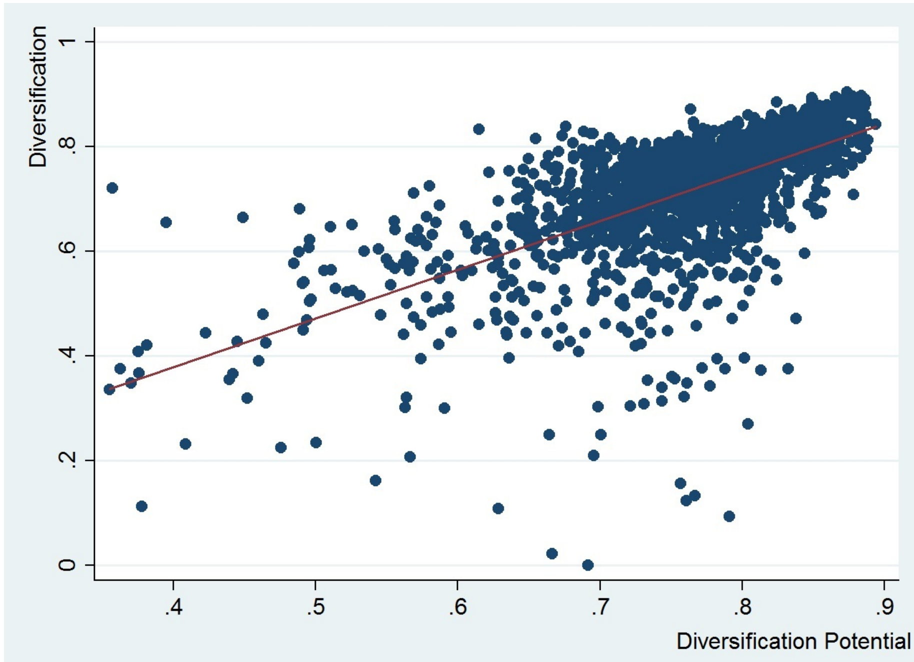
Figure 6. Shares of Selected Crops: Actual and Predicted



of potential diversity can be a good predictor of actual diversity. The scatterplot of the latter variable against the former in Figure 7 seems to indicate high predictive power in this sample. Figure 8 shows the spatial distribution of potential diversity.

The validity of the exclusion restriction –that agricultural potential diversity only affects development outcomes through actual agricultural diversity– may be a subject of concern. One source of concern is whether the measures of land productivity capture actual agricultural production conditions rather than exogenous geographic characteristics.

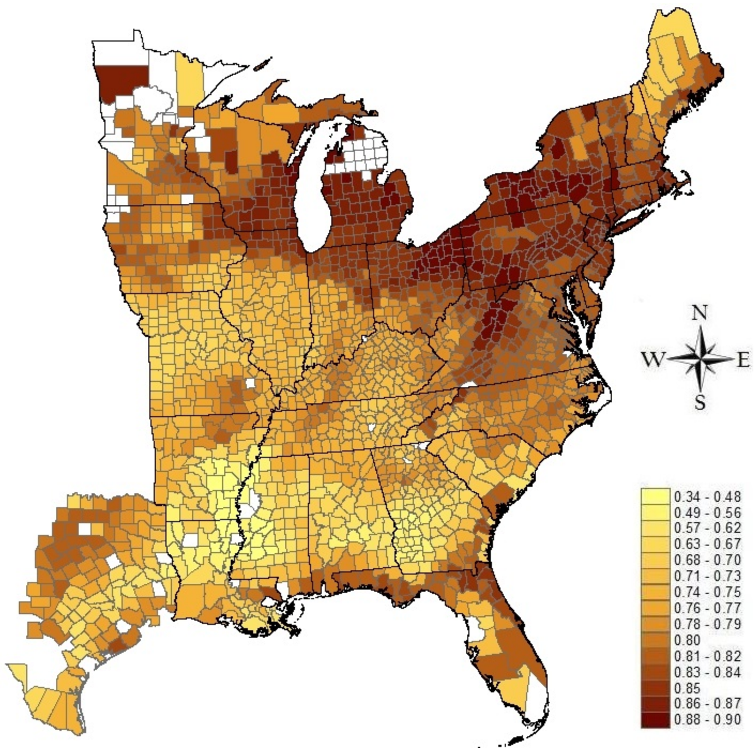
Figure 7. Agricultural Diversity: Actual and Potential



In this sense, it is important to emphasize that these measures are calculated from climate data and specific knowledge of agricultural production processes and not from statistical analysis of actual production patterns around the world.

Another source of concern is that the coefficients of the crop choice model obtained from the FML estimation may be a function of variables that affect development not only through the agricultural production mix. However, this is precisely why many observable variables that could potentially improve crop choice predictions (e.g., distances to main cities, socio-economic variables) are left out from the FML model; the effects of all the determinants of crop choice other than the productivity measures included as explanatory variables are captured by the residuals of the FML model, and thus do not interfere with the 2SLS estimation of the effects of agricultural diversity. Even so, the FML coefficient estimates could capture more than geographical conditions if there are similar spatial autocorrelation patterns not only in agricultural production and in GAEZ productivity measures but also in socio-economic variables. However, the fact that latitude, longitude and state fixed effects are included in the estimating equation but not in the FML model should alleviate this concern.

Figure 8. Agricultural potential diversity



4.2 IV Estimates

I estimate the effect of agricultural diversity using potential diversity (contructed as explained above) as an IV.[16] Table 3 reports the 2SLS 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.

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

[16]To account for the presence of a generated instrument, standard errors for the IV estimates have to be computed using a bootstrap method; this is has not been done for this preliminary draft.

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.

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 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.

Figure 9 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 (i.e., controlling for X_c and Δ_c, but not $M_{c,1860}$)). 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.

Table 3. 2SLS estimation

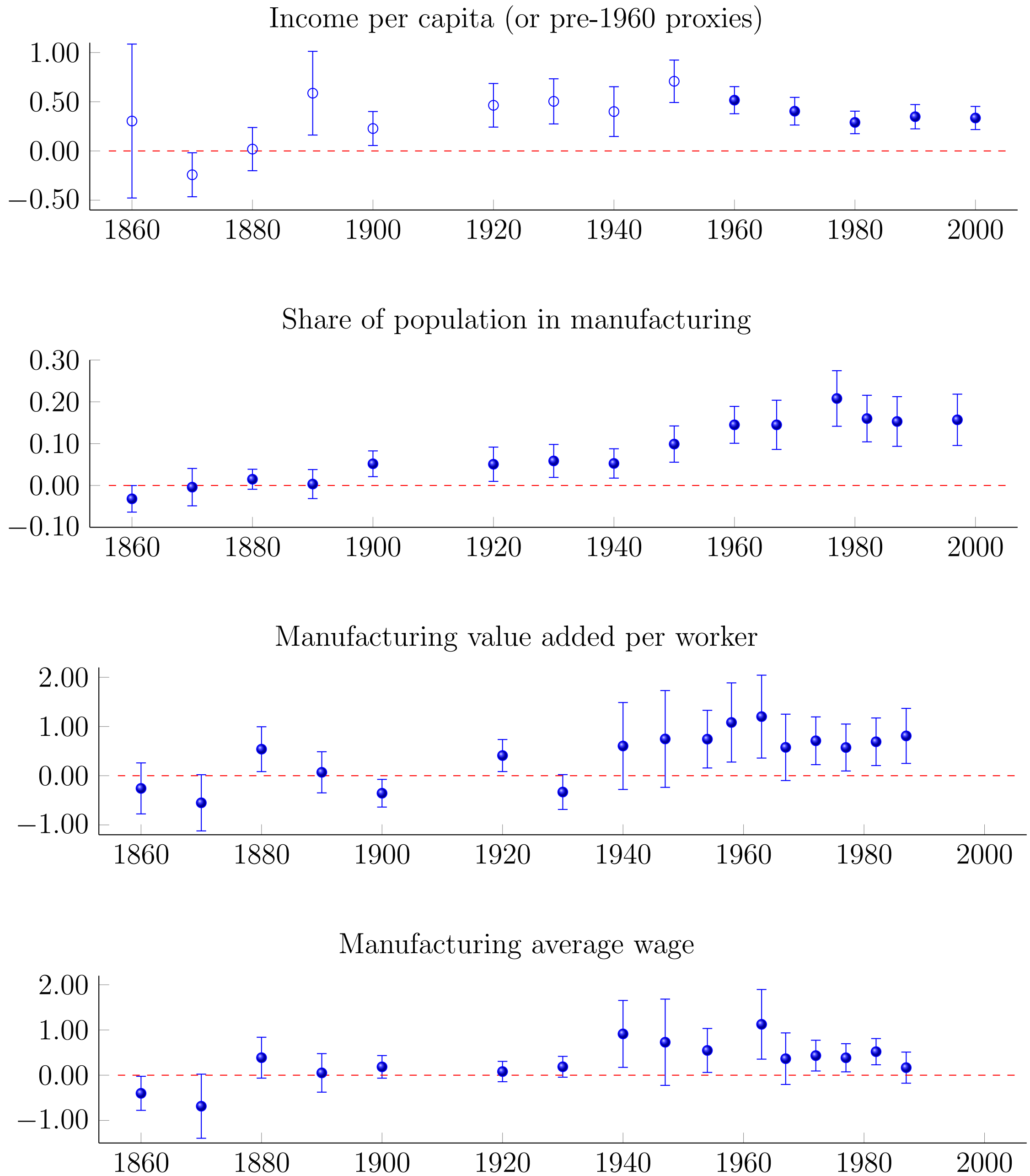
	Specification 1		Specification 2		Specification 3	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Second Stage. *Dependent variable: Ln Personal Income per capita 2000*						
Agri.Diversity$_{1860}$	0.547***	0.866***	0.333***	0.425***	0.287***	0.417**
	(0.0781)	(0.117)	(0.0564)	(0.105)	(0.0609)	(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*						
Agri.Diversity$_{1860}$	0.0985***	0.161***	0.0423***	0.0519**	0.0289**	0.110**
	(0.113)	(0.214)	(0.0910)	(0.206)	(0.0845)	(0.253)
R^2	0.087	0.052	0.480	0.082	0.618	0.292
Panel C. First Stage. *Dependent variable: Agricultural diversity 1860*						
potential 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

Robust standard errors clustered by state in parentheses

* p<0.10, ** p<0.05, *** p<0.01

See pages 11-12 for an explanation of control variables

Figure 9. The effects of early agricultural diversity on development outcomes over time (IV estimates)



Notes: The graphs display the estimated coefficients of regressions for different outcomes variables on agricultural diversification 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 Technological Dynamism in the American Industrial Take-Off

The evidence indicating long-term positive effects of agricultural diversity prompts the question: what was the channel? 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 development operated through manufacturing productivity gains associated with increased variety of industrial products and skills, formation of novel productive capabilities, and technological dynamism. Although these channels are distinct, they are tightly connected and largely complementary. The analysis below provides evidence regarding their joint plausibility without attempting to disentangle quantitatively their relative contributions.

My approach consists in estimating the impact of early agricultural diversity in key intermediate variables capturing these 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 a series of variables reflecting industrial performance at the culmination of that key historical period (Appendix C shows results for outcomes at different times).

Other channels that may explain the effects of agricultural diversity on development are examined in Section 6. 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 stands in contrast with the significant impact on industrial outcomes shown before – thus highlighting the cross-sectoral nature of the effects of early agricultural diversity. Elucidating the workings of this 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 diversification, they also shed light on the effects of agricultural diversity in the context under study. These mechanisms could have been activated by diversity in agricultural activities, as suggested by some illustrative examples mentioned by below. They could also have been activated by manufacturing diversity induced by initial agricultural diversification –as discussed below, 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 cross-sectoral linkages 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 set of (agricultural) things at early stages of development could lead to a more diverse set of (industrial) things later on.

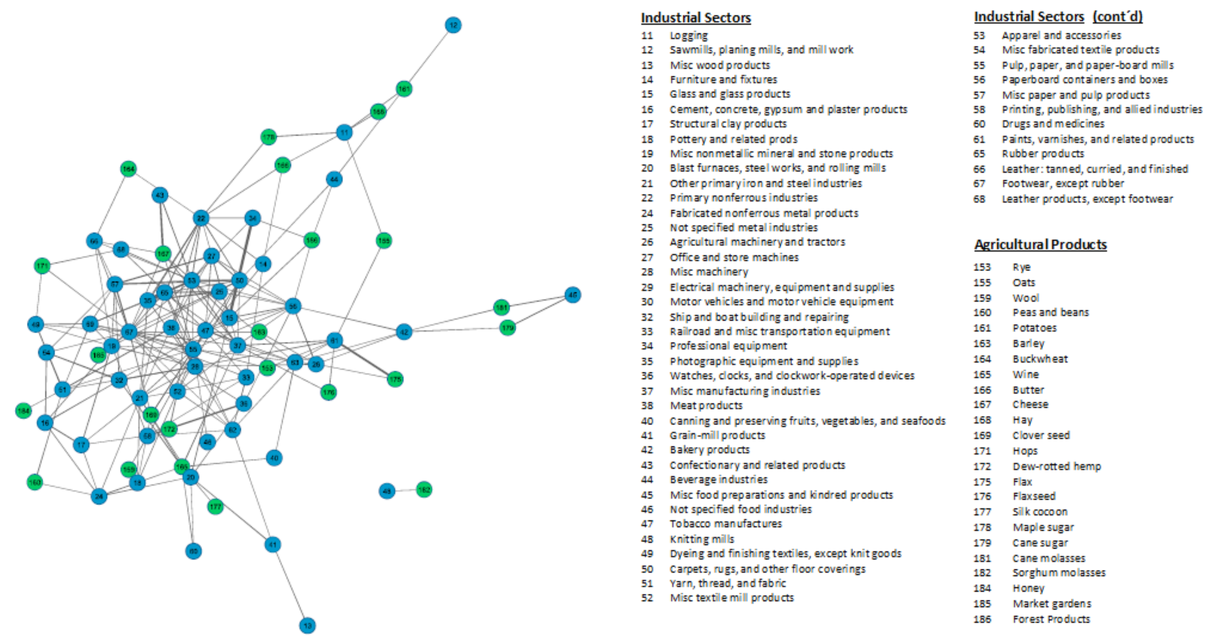
Page and Walker (1991) document a number of linkages between different agricultural products and industrial sectors in the US in the late nineteenth century, with a focus on the "agro-industrial revolution" in the American Midwest. Flour milling, the nation's largest industrial sector in production value 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 also of a range of activities that used leather.

In turn, agro-processing industries –which accounted for a large share total consumption demand and were technologically progressive– 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 realtionships as well as by common labor skills or knowledge spillovers, as emphasized by Ellison et al. (2010) in their study of industry coagglomeration patterns. Going back to Marshall (1895), the costs of moving goods, people and ideas can all be be reduced by agglomeration, thus providing different sources of industry collocation. Looking at recent (1987) plant-level data from the U.S. Census of Manufacturing (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 coagglomeration patterns.

For illustration purposes, Figure 10 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 D 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;[17] (2) agricultural products are scattered throughout the network. The implication is that various agricultural products provided different "entry points" into the industrial sectoral network of production.

Figure 10. Agricultural products and the network structure of production



Notes: The network is defined by the collection of (statistically significant) pairwise correlations between sectoral employment shares across counties in the sample in 1860, and the visual arrangement relies on a spring-embedded type of algorithm. A link between two sectors reflects a positive and significant correlation (at the 5% confidence level) and the link's thickness reflects the correlation's magnitude. 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 manifold linkages of agricultural products, Panel A of Table 5 shows positive and significant impacts on a measure of diversity across manufacturing

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

sectors in 1920.[18] I report OLS and IV estimates for the same three specifications used before.

Table 5. From agricultural diversity to industrial diversification across sectors and skills

	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)
Observations	1,676	1,676	1,676	1,676	1,676	1,676
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)
Observations	1,676	1,676	1,676	1,676	1,676	1,676
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

Robust standard errors clustered by state in parentheses

* p<0.10, ** p<0.05, *** p<0.01

See pages 11-12 for an explanation of control variables

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.

A broader array of productive activities could yield efficiency gains under imperfect substitutability between inputs, as in endogenous growth models with expanding varieties

[18] Like other outcome variables considered in this section, the index sectoral diversification (see details in Table 5's notes) is computed with employment data from the 1% sample of the Census, which report dissaggregated manufacturing employment data with at least individual 1,676 counties, so the remaining 145 counties in the sample have missing data for these indexes. Attrition is not random in the sense that missing data is more common with relative small numbers of industrial workers; however, the main results presented so far (i.e. those reported in Tables 2, 3 and 4) are qualitative the same if the estimating equations are run for the reduced sample of 1,676 counties with dissaggregated manufacturing employment data.

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 requires 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.

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 5.

The positive effects of diversity may also have to do with variety in skills. A broader array of agricultural products, each associated with different productions 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. In turn, variety of skills could yield direct productivity gains (e.g., a CES production functions where specific skills are complements). Consistent with this idea, Panel B of Table 5 shows positive and significant impacts on agricultural diversity in 1860 and on an index of skill diversity in the manufacturing sector in 1920.

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 capabilities are complementary, higher levels of diversity may reflect a wider availability of 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 23 craftsmen occupations (within a total of 58) that were marginal or non-existent in 1860 but rose to prominence within the manufacuring sector by 1920. Considering each of these 23 occupations (including electricians, tool makers, auto mechanics, etc) as a specific skill, I compute a county-level measure of new skills formation as the count of these ocuppational categories that represented nonzero shares of the manufacuring labor force in 1920. Panel A of Table 6 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 6 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 effect of diversification on human capital formation in the long run.[19]

Following the insights of Jacobs (1969) and others, a more diversified economy may be more conducive to technological dynamism. As discussed in Section 2, this effect may 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 –relying 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 Revoluation were the correlative improvements in power generation and transmission networks.[20]

Some examples of complementarities and recombinant innovations from the American Second Industrial Revolution involve agricultural machinery suppliers and agro-processing industries, thus suggesting a direct link between agricultural diversity and technological dynamism. Production of agricultural implements in the mid-nineteenth century, which was still characterized by small and medium establishments serving local markets, 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

[19] 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).

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

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. Complementarities between technologies in this sector and other industries were also important; the development of the plow, for instance, relied heavily on advances in iron metallurgy (Pudup, 1987). Finally, as suggested by the history of Ford Motors Company, the concept of the production chain incorporated insights from flour mills, meat-packing establishments, breweries and canning factories (Hounshell, 1985).

Table 6. Effects of 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+ year, 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)
Observations	1,821	1,821	1,821	1,821	1,821	1,821
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

Robust standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

See pages 11-12 for an explanation of control variables

To assess the relevance of this mechanism, 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.[21] I interpret the county-level patent counts as proxies for local

[21] The patents data, which reports the location of each innovator, comes from Akcigit et al. (2013); I am

technological dynamism broadly defined, capturing not only innovation but also adoption and adaptation to local environments (as a matter of fact, many of the innovations introduced in patents were unsuccessful, and only few of them led to actual shifts in the national technology frontier). The estimates of the effects of early agricultural diversification from Tobit models, reported in Panel C of Table 6, 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).

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. As shown by Henderson et al. (1995), Jacobs externalities can be particularly important for the development of high-tech industries: in a study of industrial development in US between 1970 and 1987, they 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.

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 share of manufacturing workers in county c employed in industrial sector s, and the key regressor is the interaction between early agricultural diversification at the county-level and an industry-level measure of skill- or knowledge-intensity ($\text{Agri.Diversity}_{c,1860} \times \text{Intensity}_s$). The estimating equation is

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

where α_s is an industry fixed effect and α_c is a county fixed effect. The measure of skill-intensity is the average level of education of the industry's workers, while the measure of knowledge-intensity is the fraction of engineers and scientists in total industry employment in the US economy in 1950; the results are robust to considering the fraction of non-

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.

production workers in total industry employment, another standard measure of knowledge-intensity.

Table 7 shows regression estimates for the different specifications. In all cases, there is a positive significant effect of early agricultural diversity in the development of skill-intensive and knowledge-intensive industries.[22]

Table 7. Differential effect on skill- and knowledge-intensive sectors

	Dependent variable: share of industrial workers in county c employed in sector s			
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Agri.Diversity$_{c,1860}$×Skill-Intensity$_s$	0.00409***	0.00711***		
	(0.000735)	(0.00106)		
Agri.Diversity$_{c,1860}$×Knowledge-Intensity$_s$			0.467***	0.937***
			(0.010)	(0.131)
R^2	0.141	0.141	0.141	0.141
Sector and county 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

Robust standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

6 Other mechanisms

6.1 Agricultural Productivity and Labor Push

Section 5 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 an effect of agricultural diversity on agricultural productivity that

[22] 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).

"pushed" labor out of agriculture? The the literature on structural change has devoted considerable attention to the relative contribution of manufacturing productivity growth and agricultural productivity growth to the advance of industrialization (e.g., Alvarez-Cuadrado and Poschke, 2011). For this channel to be operative, the 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 have consistent signs. This subsection discusses how those links may operate and examines each of them empirically in the context under study; 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). Diversification 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 points estimates are positive, the estimates do not indicate that a significant effect of agricultural diversification 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 and cheaper inputs for industrial 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.[23] 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

[23] 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).

IV estimates of the effects of agricultural productivity in 1860 on the share of population employed in manufacturing in 1920. The 2SLS estimates uses 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. Overall, the results presented in Table 8 do not provide much support the relevance of the agricultural productivity channel.

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)
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)
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

Robust standard errors clustered by state in parentheses

* p<0.10, ** p<0.05, *** p<0.01

See pages 11-12 for an explanation of control variables

6.2 Volatility, Risk and Local Financial Development

The 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).

In contrast, it is possible that places that were not well-suited to limit volatility through diversification resorted to the development of local banking systems, which in turn have positive effects on development through channels other than risk management (e.g., by chanelling savings to productive investments more effectively). 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 in the US.

While diversity would lower volatility and thus reduce credit demand, it could also have a contrasting effect on local financial development by positively affecting credit supply. A diverse local economy allows banks to reduce risk exposure by funding a wide array of imperfectly correlated projects, thus increasing financial intermediation (see Ramcharan, 2010b, who calls this the "production structure hypothesis").

I begin by assessing the idea that under incomplete financial markets volatility may hinder the emerging industrial sector. I use the year-to-year evolution of prices at the national levels over the period to construct a measure of volatility that depends on the predicted mix of agricultural products of each county at the beggining of the period. I use country-level data on the prices of 16 products which are available from 1866 to 1919 and comprise over 93% of total agricultural production in 1860 in the sample. Fixing the predicted shares of products at 1860 levels, 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 this 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.[24]

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

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

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)
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)
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	1,820	1,821	1,820	1,821	1,820

Robust standard errors clustered by state in parentheses

* p<0.10, ** p<0.05, *** p<0.01

See pages 11-12 for an explanation of control variables

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 initial predicted shares and subsequent national prices. $St.Dev.(Gy^{\mathrm{a}}_{ct})$ is its standard deviation

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 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 these 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 diversification. 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 previous footnote 16). 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, a commonly used measure of local financial development in that period.

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)
$\text{Agri.Diversity}_{1860}$	0.00801	0.0321	-0.0400	0.110	-0.0618	-0.111
	(0.157)	(0.333)	(0.0696)	(0.159)	(0.0530)	(0.v)
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

Robust standard errors clustered by state in parentheses

* p<0.10, ** p<0.05, *** p<0.01

See pages 11-12 for an explanation of control variables

6.3 Land Concentration and the Political Economy of Education and Banking

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 larger farm sizes than places with low potential diversity. In addition, the benefits of diversification due to economies of scope may decline with size (Chavas and Aliber, 1993).

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 signifficant adverse effect on educational expenditures; this was a period characterized by a massive expansion of secondary education, which was key for the transition from agriculture to modern industry –as suggested by the model presented in their paper–. 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 that –again in the early twentieth century– US counties with higher land inequality had significantly 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 have limited access to credit due to insufficient collateral (e.g., Chakraborty and Ray, 2007).[25]

Did agricultural diversity lower land concentration? 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.[26] 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

[25]Adamopoulos (2008) also argues that land concentration can hinder industrialization, insofar as the landed elite can influence government policies to protect its rents in the rural economy. In his model, the policy that blocks industrialization is a tariff on the imports of intermediate inputs required by manufacturing production. A quantitative application of the theory is developed to illustrate how the divergence between the growth paths of Argentina and Canada may be explained by their different initial degress of inequality in land ownership. Naturally, this mechanism is less relevant when comparing development paths across US counties.

[26]The results are qualitatively similar –although not robust across all specifications– if the outcome variable is replaced by the share of land corresponding to alternative thresholds in farm size, or by the share of land corresponding to the largest 5%, 10% or 20% of farms.

higher levels 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 6.1 shows no significant effects of early agricultural diversification on bank density in 1920. Likewise, the evidence does not support the idea that it may have positively affected educational investments. Table 12 shows results from regressions of school expenditures per capita in 1890 and 1932 on agricultural diversity in 1860; its estimated effects flip sign and are not consistently significant across specifications.

Table 11. The effects of diversity on land inequality

	Specification 1		Specification 2		Specification 3	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Panel B. *Dependent variable: Share of farmland in farms over 500 acres 1920*						
Agri.Diversity$_{1860}$	-0.319***	-0.304***	-0.167***	-0.157***	-0.119***	-0.153*
	(0.0715)	(0.0741)	(0.0323)	(0.0500)	(0.0364)	(0.0929)
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

Robust standard errors clustered by state in parentheses; * p<0.10, ** p<0.05, *** p<0.01

See pages 11-12 for an explanation of control variables

Table 12. Effects of agricultural diversity on public schooling

	Specification 1		Specification 2		Specification 3	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. *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)
Panel B. *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)
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

Robust standard errors clustered by state in parentheses

* p<0.10, ** p<0.05, *** p<0.01

See pages 11-12 for an explanation of control variables

7 Conclusion

This paper shows that agricultural production patterns on the eve of 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 diversification in 1860 can be traced back to the advance of the industrialization process in the early 20th century (as measured by the share of population employed in manufacuring in 1900). Thus, the evidence suggests that early agricultural diversity affected long-run growth by shaping patterns of structural change over the course a key historical period of economic transformation.

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. Specific specialization patterns are also controlled for with alternative sets of variables capturing the dominance of particular agricultural products. The inclusion of distances to water and cities and a measure of market potential 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 initial conditions (i.e., 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 natural endowments. Using crop-specific climate-based productivity measures, I estimate a fractional multinomial logit model derived from optimal crop choice and then construct a measure of potential diversity. The predicted shares obtained from the estimation of this model display a good fit with actual shares for most agricultural products, and the index of potential diversity explains a large fraction of the variation in actual diversity. The index of potential diversity is used as IV in the estimation of the effects of agricultural diversity on development outcomes as well as on different variables capturing potential mechanisms through which early agricultural diversity may have affected the transition from agriculture to industry.

The evidence suggests that the positive impact of agricultural diversity operated through manufacturing productivity rather than agricultural productivity. Futhermore, the results indicate that productivity gains in manufacturing may have arisen from higher industrial diversity, accelerated acquisition of new skills and enhanced technological dynamism. Beyond showing positive and significant impacts of early agricultural diversity on key intermediate variables, I establish the relevance of these channels by testing a cross-county cross-industry implication: diversification in agriculture had a positive differential impact on skill-intensive and knowledge intensive industrial sectors.

In contrast, the evidence does not support the relevance of other mechanisms. 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 initial composition and the evolution of prices at the national level. The results are do are not consistent with the relevance of this channel. I also assess political economy mechanisms that may have operated at the local level by examining the impact of early agricultural diversification on intermediate variables capturing these channels. I find a negative effect of early agricultural diversification on land concentration, but no evidence of impacts on local financial development nor on local educational expenditures.

The evidence suggests that early agricultural diversity increased the relative size and productivity of the manufacturing sector by enhancing the variety of inputs and skills, human capital formation, and technological dynamism. I do not find evidence indicating a positive effect on agricultural productivity nor a positive effects operating through reduced volatility in the value of agricultural production. Early agricultural diversification was associated with lower degrees of land concentration, but there were no significant effects on on financial development nor on educational expenditures.

This paper adds to the literature on the deeply-rooted determinants of comparative development by showing that agricultural resource endowments and the structure of production in the agricultural sector at early stages of development can affect the process of growth and structural change. The insights about the role of economic diversity obtained from the history of U.S. counties going back to 1860 might be relevant for understanding the long-run performance of developing countries. To further our understanding of the role of diversification and establish policy implications, future research should attempt to pin down the mechanisms through which diversification affects development outcomes as precisely as possible, and to assess the relevance of agricultural diversity for long-run outcomes in different contexts across space and time.

Appendix A. 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.

Tables A1 and A2 show OLS and IV estimates of the effects of agricultural diversity on income per capita 2000 and manufacturing productivity 1920 with alternative sets of crop-specific controls.[27] To facilitate comparison, columns 1-2 do not include any crop-specific

[27] 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.

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 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 negative effects on manufacturing productivity in 1920, but positive effects on income per capita in 2000. The absence of 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 A1. 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$_{1860}$	0.324***	0.371***	0.323***	0.342**	0.294***	0.331**	0.328***	0.341**	0.264***	0.284*
	(0.0630)	(0.106)	(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)
Observations	1821	1821	1821	1821	1821	1821	1821	1821	1821	1821
R^2	0.430	0.429	0.438	0.438	0.443	0.443	0.435	0.435	0.447	0.450
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

Robust standard errors clustered by state in parentheses; * p<0.10, ** p<0.05, *** p<0.01; See pages 11-12 for an explanation of control variables.

Table A2. The Effects of Agricultural Diversity versus Specific Specialization Patterns

	Dependent variable: Manufacturing productivity, 1920									
	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$_{1860}$	0.295***	0.410*	0.318***	0.499**	0.304***	0.524**	0.332***	0.562**	0.342***	0.781***
	(0.0935)	(0.218)	(0.0901)	(0.222)	(0.0920)	(0.236)	(0.0971)	(0.236)	(0.0925)	(0.296)
Corn			-0.0607	-0.0719	-0.0387	-0.0249	-0.0882***	-0.0934***	-0.279*	-0.119
			(0.0465)	(0.0458)	(0.0353)	(0.0358)	(0.0281)	(0.0290)	(0.152)	(0.209)
Cotton			-0.0257	-0.0246	-0.0286	-0.0300	-0.0389	-0.0307	-0.192	-0.0294
			(0.0575)	(0.0577)	(0.0347)	(0.0337)	(0.0330)	(0.0326)	(0.147)	(0.208)
Animals Slaughtered			-0.0175	-0.0365	-0.0168	-0.0325	-0.0208	-0.0309	-0.428**	-0.518***
			(0.0565)	(0.0532)	(0.0219)	(0.0259)	(0.0187)	(0.0220)	(0.158)	(0.196)
Hay			-0.0000883	-0.0102	0.0820**	0.0773**	-0.0386*	-0.0320	0.00634	0.103
			(0.0573)	(0.0540)	(0.0369)	(0.0343)	(0.0226)	(0.0237)	(0.171)	(0.199)
Wheat			-0.0656	-0.0804*	-0.0507	-0.0599**	-0.0562	-0.0596*	-0.316	-0.319
			(0.0495)	(0.0464)	(0.0303)	(0.0293)	(0.0348)	(0.0334)	(0.197)	(0.194)
Tobacco+Cane+Rice			-0.0418	-0.0589	-0.0385	-0.0439	-0.0545	-0.0588*	-0.192	-0.109
			(0.127)	(0.122)	(0.0354)	(0.0309)	(0.0368)	(0.0347)	(0.155)	(0.191)
Observations	1821	1821	1821	1821	1821	1821	1821	1821	1821	1821
R^2	0.255	0.255	0.258	0.256	0.263	0.261	0.263	0.259	0.264	0.254
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

Robust standard errors clustered by state in parentheses; * p<0.10, ** p<0.05, *** p<0.01; See pages 11-12 for an explanation of control variables.

Appendix B. Alternative Measures of Diversity

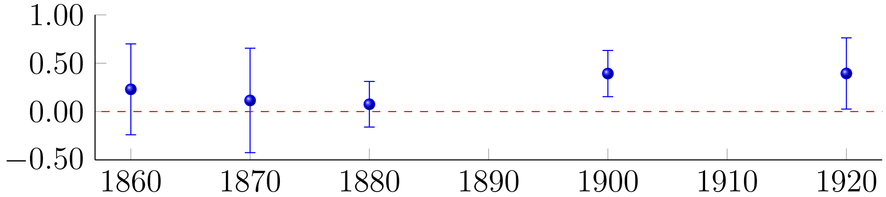
Table B1. Effects of Agricultural Diversity with Alternative Measures

	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	-0.324***	-0.371***										
	(0.0533)	(0.111)										
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)
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	0.430	0.429	0.419	0.419	0.421	0.421	0.430	0.429	0.431	0.431	0.421	0.421
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

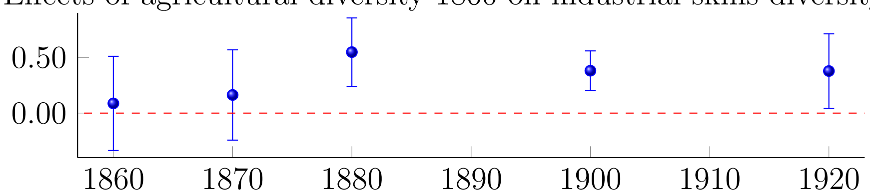
Robust standard errors clustered by state in parentheses; * p<0.10, ** p<0.05, *** p<0.01; See pages 11-12 for an explanation of control variables.

Appendix C. The effects of early agricultural diversity on intermediate variables over time

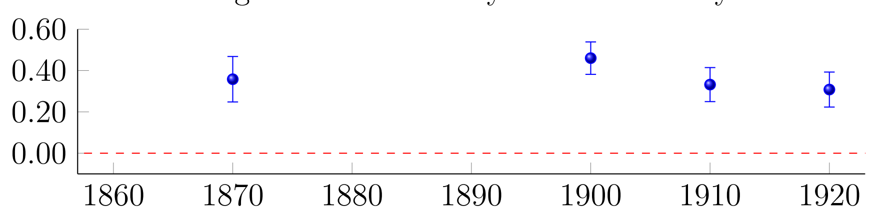
Effects of agricultural diversity 1860 on industrial diversification



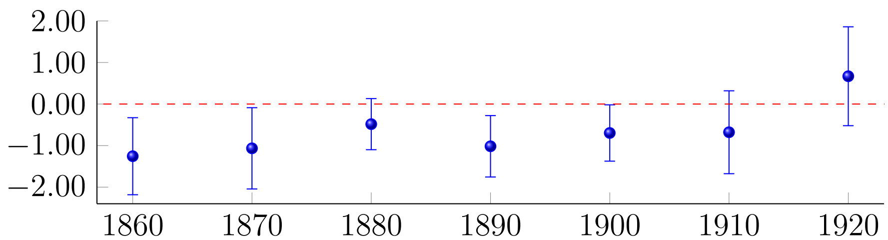
Effects of agricultural diversity 1860 on industrial skills diversity



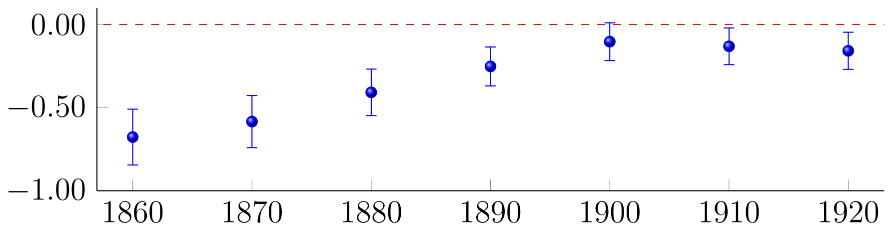
Effects of agricultural diversity 1860 on literacy rates



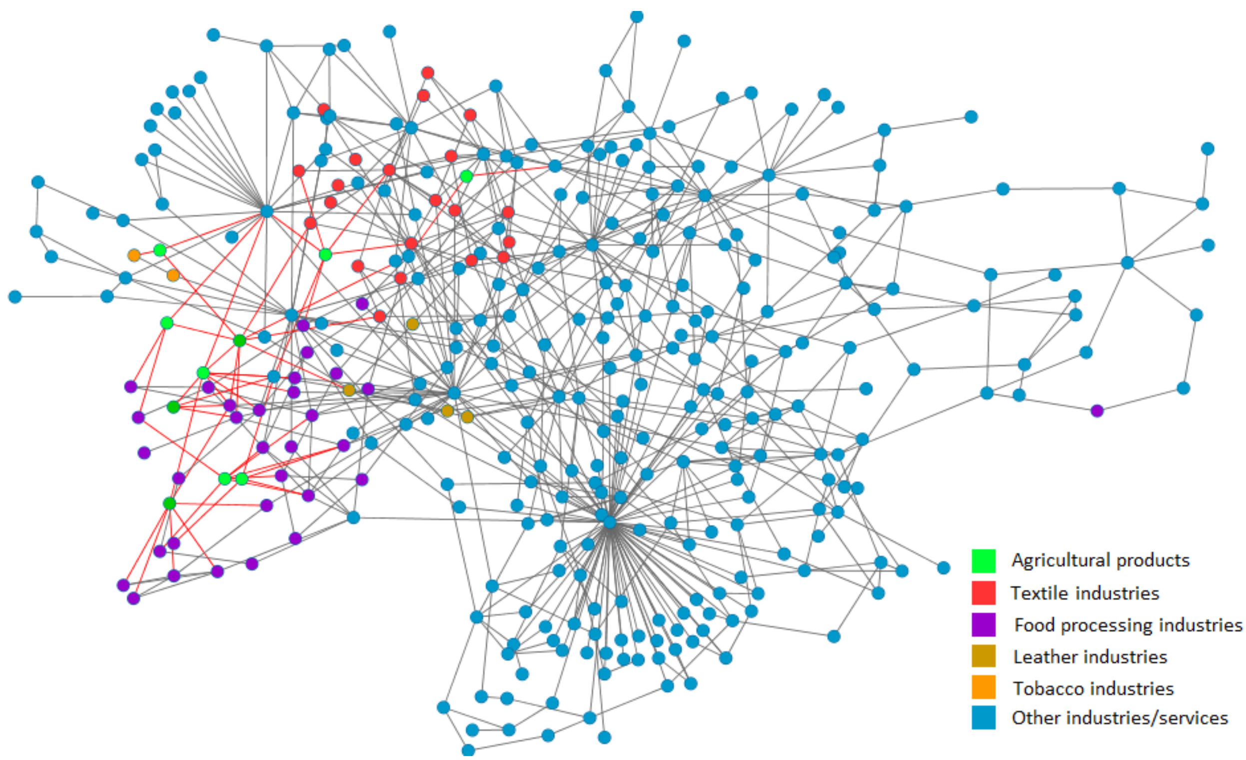
Effects of agricultural diversity on agricultural productivity



Effects of agricultural diversity on farmland share in largest farms



Appendix D. Agricultural-Industrial Linkages in the network of production



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