The Shadow of Slavery on Industrial Innovation: Evidence from the US South

Yeonha Jung[*] Chungeun Yoon[†]

Sungkyunkwan University KDI School of Public Policy

November 2022

Abstract

This study explores the imprint of American slavery on industrial innovation. We hypothesize that historical slave concentration hindered innovation activity through post-Reconstruction policies, which created labor market conditions facilitating unskill-biased technical change. County-level evidence from patent data substantiates this argument. Higher prevalence of slavery in 1860 was followed by a relative decline in patents, where this relationship became evident only after Reconstruction. The reduction in innovation was more pronounced in low-skill industries, which were better suited to unskill-biased technical change. Moreover, evidence shows that skill demands in the industrial sector decreased with historical slave concentration after Reconstruction, which corroborates the impact of slavery on the shift of production technology. Contrary to the marked influence of slavery on industrial innovation, we do not find a comparable pattern in agriculture that had long been dependent on slave labor.

Keywords: Slavery, post-Reconstruction, innovation, unskill-biased technical change

JEL Codes: H11, N41, O33

[*]Assistant Professor at the Department of Economics. Email: yhjung0408@skku.edu

[†]Assistant Professor. Email: cyoon@kdis.ac.kr

1 Introduction

Slavery has left a profound imprint on the US South. The literature demonstrates the pervasive legacy of slavery on southern economic development, which are represented as reduced human capital, lower income, and increased economic inequality (Sokoloff and Engerman, 2000; Engerman and Sokoloff, 2002; Nunn, 2007; Bruhn and Gallego, 2012; Bertocchi and Dimico, 2014). This study extends our understanding of the lasting impact of slavery with a focus on innovation, which is an essential factor in long-run growth and development (Aghion and Howitt, 1992; Klette and Kortum, 2004; Gordon, 2016; Akcigit and Kerr, 2018).

The direction of technical change is contingent on labor market conditions such as relative wages (e.g. Acemoglu, 2002; Aaronson and Phelan, 2019), skill-mix (e.g. Hunt and Gauthier-Loiselle, 2010; Lewis, 2011), or demographic structures (e.g. Parrotta et al., 2014; Acemoglu and Restrepo, 2022). In the context of slavery and innovation, employment conditions could have been a critical factor. The partial persistence of the hierarchical regime of slavery even after its abolition may have hindered skill-biased technical change by facilitating the exploitation of cheap unskilled labor (Ransom and Sutch, 2001; Woodman, 1977).

However, labor market conditions in the postbellum South were not constant over time. While Reconstruction encouraged the integration of freed Blacks after the Civil War, this process was terminated in the late 1870s, followed by institutional reproduction of the antebellum hierarchy. Furthermore, recent studies find that historical slave concentration caused variation in local implementation of post-Reconstruction polices. Counties with a higher prevalence of slavery in the past applied post-Reconstruction policies more intensely, which promoted the restoration of the antebellum hierarchy (Suryanarayan and White, 2021; Jung, 2021).

In this context, we hypothesize that a negative link between slavery and innovation in the postbellum South emerged after Reconstruction. Considering that innovation in the postbellum America was primarily in a labor-saving direction (Wright, 1987; James, 1983; George, 2012), the interaction between slavery and post-Reconstruction policies, which created labor market conditions more suitable for exploiting unskilled labor, is expected to have hindered innovation activities. The suggested mechanism provides two additional testable predictions. First, innovation associated with agriculture would have been less susceptible to this effect. Given that historical slave concentration indicates heavy reliance of the agricultural production on forced labor, post-Reconstruction policies would have been more of a return to the previous order in agriculture, not the emergence of new environment for production. Second, the legacy of slavery would have been heterogeneous even within the industrial sector. Based on labor market conditions, we expect the post-Reconstruction decline in innovation to be more pronounced in low-skill industries, which were better suited to unskill-based technical change.

For empirical analysis, the extent of innovation is proxied by the number of patents obtained from the HistPat database, which we normalize by the size of the relevant population depending on specifications. Using the slave-to-population ratio in 1860 as a measure of historical slave concentration, we investigate the changing relationship between slavery and innovation across southern counties with a continuous difference-in-differences approach. To address the potential endogeneity of slavery, we suggest an instrumental variable (IV) strategy that exploits the exogenous variation in crop mix. Using the fractional multinomial logit (FML) framework, we identify variation in the production of the slave crops (cotton, tobacco, rice, and sugarcane) that is attributable exclusively to the distribution of climate-based crop suitability. The exogenous variation in the share of the slave crops is employed as the IV for the prevalence of slavery. The placebo test supports the exclusion restriction of our IV strategy, showing that the agro-climatic variation in the slave crops was not tied to innovation in non-southern counties that did not share a history of slavery and post-Reconstruction polices.

The evidence substantiates our hypotheses. While both the OLS and IV results indicate a negative link between slavery and patents in the postbellum period, this relationship was not evident until the end of Reconstruction. When the sample period is restricted up to 1880, the impact of slavery on the postbellum decline in innovation vanishes, which indicates that the shadow of slavery on innovation did not arise immediately after its abolition, but rather emerged after Reconstruction. To validate the pivotal role of the post-Reconstruction period further, we estimate another specification that considers only the post-Civil War years as the sample period. Even with the postbellum sample, we find that the difference-in-differences estimate using post-Reconstruction as the treatment period is significantly negative. This confirms that the post-Reconstruction period was a critical juncture in the rise of the negative link between slavery and innovation.

The results also support the two additional predictions of our hypothesis. First, the post-Reconstruction relationship between slavery and patents was not pronounced in agriculture. Based on the cooperative patent classification (CPC) codes, we construct the number of manufacturing and agricultural patents per worker as outcome variables. Contrary to the relative decline in manufacturing patents with slavery after Reconstruction, the association between slavery and agricultural patents is shown to be stable over time. The coefficients are statistically insignificant and close to zero in all specifications, which indicates that the dynamics of agricultural innovation were not tied to the local history of slavery.

Second, even within manufacturing, the legacy of slavery was more pronounced in low-skill industries. The classification of low- and high-skill industries rests on the composition of occupational skill levels, which are proxied by the EDSCOR50 variable in the census data. By matching the CPC codes with the industrial classification of the decennial census (IND1950), we count the number of manufacturing patents associated with low- and high-skill industries, respectively, which is normalized by the size of the relevant workforce. The results confirm heterogeneity within the industrial sector. After Reconstruction, historical slave concentration was followed by a decline in patents associated with low-skill industries, but the relationship between slavery and high-skill patents did not significantly change.

The timing of evidence and its heterogeneity by sector and industry dovetail with our hypothesis. As a further test, we explore the relationship between slavery and the demand for skills over time. If the negative link between slavery and innovation hinged on the role of post-Reconstruction policies facilitating the use of unskilled labor, it should be accompanied by reduced demand for skilled workers. The demand for skills is proxied by the return to literacy, which represents the likelihood of literate workers having skilled occupations. After estimating the return to literacy in manufacturing using the complete-count census data, we find that slavery induced a reduction in the return to literacy of industrial workers after Reconstruction. Moreover, this effect is evident only in low-skill industries, which supports our hypothesis.

Our findings on the relationship between slavery and patent trends add to the literature on the institutional determinants of innovation. Along with the roles of institutions in economic development (e.g., Acemoglu et al., 2001; Banerjee and Iyer, 2005; Acemoglu and Robinson, 2012b; Guiso et al., 2016), the institutional roots of innovation have been investigated in diverse aspects. For example, Khan and Sokoloff (2004) suggest a historical link between the democratic patent system and American innovation, which echoes the findings of MacLeod (2002) in the context of the British Industrial Revolution. Evidence is not limited to the patent system. Using the French occupation in Imperial Germany, Donges et al. (2022) explores the lasting impact of inclusive institutions on innovation, and Acemoglu et al. (2016) find a positive relationship between bureaucratic capacity and patenting in the 19th century US. Our study extends these views by focusing on the dynamics of the institutional roots of innovation, which sheds light on the formation of the long-term relationship.

Additionally, the mechanism of the reduced innovation contributes to the literature on endogenous changes in factor-biased technologies. In accordance with the theories of directed technical change (e.g., Aghion and Howitt, 1996; Acemoglu, 1998, 2002), empirical studies demonstrate the relationship between the relative factor supply and technological progress. Manuelli and Seshadri (2014) document that lower wages delayed the diffusion of tractors, and analogous results are found in relation to the relative supply of low-skilled labor (Hornbeck and Naidu, 2014). Correspondingly, a series of studies explores technological responses to immigration shocks that changed the skill mix (Lewis, 2011; Peri et al., 2015; Carneiro et al., 2018; San, 2022). Adding to the studies focusing on the effects of the relative factor supply, our evidence on the relationship between slavery and the return to literacy suggests that changes in institutional conditions can also cause factor-biased technical change

Finally, this study provides a novel perspective on the long-reach of American slavery. Following the influential works of Engerman and Sokoloff (Engerman and Sokoloff, 1994; Sokoloff and Engerman, 2000; Engerman and Sokoloff, 2002), a large literature has investigated the lasting imprint of slavery on the US economy in various aspects such as local development (Nunn, 2007; Bruhn and Gallego, 2012), racial inequality (O'Connell, 2012; Bertocchi and Dimico, 2014; Jung, 2021), and economic mobility (Sacerdote, 2005; Berger, 2018). Our evidence on the relationship between slavery and industrial innovation extends the perspectives of this line of study. Furthermore, we show that the negative link between slavery and innovation emerged only after Reconstruction. This suggests that beyond its persistence, the legacy of slavery can be thoroughly understood only when its dynamic aspects are considered together.

The remainder of this paper is organized as follows. Section 2 discusses historical background and the hypothesis of this study. Section 3 provides the supporting evidence, and Section 4 addresses its mechanism. Section 5 concludes the paper.

2 Conceptual Approach

This study argues that the historical prevalence of slavery induced slowdown in industrial innovation after Reconstruction. As historical background, Section 2.1 discusses the relationship between slavery and labor market conditions in the postbellum South, and Section 2.2 addresses its potential link to innovation. Based on this, Section 2.3 specifies testable hypotheses.

2.1 Slavery and Labor Market Conditions after the Civil War

The labor market in the postbellum South experienced significant institutional changes. Among these, Reconstruction was a critical juncture. As our hypothesis hinges on the historical relationship between slavery and post-Reconstruction labor polices, this section discusses how the beginning and end of Reconstruction impacted the labor market in the South.

After the Civil War, Reconstruction policies were implemented in the South to promote the transition of the forced labor system into a free-labor economy. The institutional intervention of the Freedmen's Bureau played a crucial role in this process, organizing and supervising labor contracts to ensure fair labor practices (e.g., Bentley, 2017; Rogowski, 2018), providing educational resources for African Americans (e.g., Anderson, 1988; Margo, 2007), and supporting the mobility of Black workers (e.g., Cohen, 1984; Thomas et al., 2017). The political clout of African Americans was another critical factor. The legislative changes advanced the political influence of Blacks significantly, which contributed to improving the socioeconomic status of African Americans (Foner, 1988; Logan, 2020).[1]

However, this process was derailed with the end of Reconstruction.[2] Institutional conditions changed in the post-Reconstruction South to restore the hierarchical labor market. The enforcement of the Black Codes, a set of laws passed after the Civil War to maintain control over freed African Americans, was one of the most central instruments.[3] The laws were invalidated by Reconstruction policies, but regained their effectiveness afterward. A key role of the Black Codes was to limit the labor mobility of Blacks (Wilson, 1965; Clarke, 2018; Naidu, 2010). For example, vagrancy laws and anti-enticement laws forced Black workers to accept adverse working conditions, and apprentice laws expanded such effects to younger generations.[4] Along with the Jim Crow laws, which were mainly

[1] The Reconstruction amendments guaranteed the political rights of freed Blacks, and the Bureau encouraged Black political participation in various ways, assisting voter registration or providing political education (Cunningham, 1991).

[2] In 1877, an informal deal was made to resolve the dispute over the votes in the 1876 presidential election. Through this deal, the Republican candidate took the disputed votes and withdrew the last federal troops from the South in return. This marked the end of Reconstruction and restored Democratic control in the South.

[3] Even before the Civil War, there were slave statues and many other laws to regulate free Blacks. The Black Codes can be understood as an extension of such laws.

[4] While their specific details differ across states and periods, vagrancy laws criminalized being unemployed, and anti-enticement laws prohibited hiring or suggesting more favorable contracts to those under another contract. As these laws were de facto targeted at Blacks, occupational and spatial mobility of Black workers was bound to be significantly limited. Apprentice laws enabled White employers to "apprentice" Black children who were not supported by their parents. Since children whose parents had committed crimes were subject to the laws, they allowed intergenerational control of the black labor force (Richardson,

put into place from the late 19th century, the South could maintain the hierarchical labor market and exploit Black workers as cheap unskilled labor (Cohen, 1976; Roback, 1984; Wright et al., 1986).[5]

While the re-emergence of the hierarchical labor market was a southern phenomenon, its extent varied even within the South. The historical prevalence of slavery was a key determinant of the spatial variation. As the abolition of slavery implied the collapse of the means of production, the Civil War had a disproportionate impact on slaveowners (Goldin and Lewis, 1975; Ager et al., 2021), which suggests that the incentive to resolve the labor problem due to emancipation increased with previous dependence on slave labor. Thus, when appropriate institutional conditions were established after Reconstruction, formerly slave-intensive regions exploited post-Reconstruction policies more effectively to exploit Black workers.

Empirical evidence supports the above premise. Jung (2021) finds that anti-enticement laws, which were an essential instrument of the Black Codes, were more intensely applied in slave-intensive counties to keep Blacks as cheap unskilled labor. Suryanarayan and White (2021) provide evidence that historical slave concentration led to a relative decline in bureaucratic capacity, where this relationship is observed only after Reconstruction. The authors interpret that bureaucratic weakening resulted from the motivation of local elites to hinder the integration of African Americans, which echoes the selective application of labor policies.

2.2 Post-Reconstruction Policies and Innovation: Potential Link

Changes in labor market conditions could affect innovation activity. In the context of the postbellum South, we can think of two potential channels for this relationship. First, institutional environment affects the relative cost of inputs. As discussed in Section 2.1, post-Reconstruction policies strengthened control over Black workers, which implied a relative decline in the cost of low-skilled labor. In the theoretical framework of Acemoglu (2010), a decline in the relative price of labor reduces innovation when technology is labor-saving, where this condition matches the industrial environment in the South at the time.[6] Historical records document that innovation in postbellum America was invariably

1969).

[5]Changes in social and political institutions also had profound effects on the economic status of Black workers, especially through the human capital channel. Following disenfranchisement, the quantity and quality of educational inputs for Blacks declined significantly (Kousser, 1980; Margo, 1982; Naidu, 2012), which contributed to the persistence of the racial wage gap. (Margo, 2007; Carruthers and Wanamaker, 2017).

[6]The theoretical argument of Acemoglu (2010) is supported by a wide range of empirical evidence. For example, in historical contexts, Manuelli and Seshadri (2014) suggest a negative effect of wage on adoption

in a labor-saving direction (e.g., Wright, 1987; George, 2012), and James (1983) and Cain and Paterson (1981) provide corresponding evidence based on the late 19th and early 20th century US manufacturing. In consideration of the contemporary technological environment, we expect that post-Reconstruction labor policies had adverse effects on innovation.

Institutional quality could be more broadly considered as an alternative channel. The end of Reconstruction was a shift from short-lived inclusive institutions to an extractive regime, where the latter has been thought to discourage incentives of elites and entrepreneurs to invest in innovation (North and Thomas, 1970; Acemoglu and Robinson, 2012a). Empirical evidence supports the conceptual link between institutional quality and innovation activity. For example, Sokoloff (1984) argues that the transition of artisan shops to non-mechanized factories in US manufacturing did not involve any technological innovation because it was the result of labor exploitation based on extractive institutional arrangements. Donges et al. (2022) report a consistent finding that the French occupation in Imperial Germany increased the number of patents by replacing exclusive institutions with inclusive institutions. In this context, the extractive nature of post-Reconstruction policies could have created an unfavorable environment for innovation.

2.3 Hypotheses on the Relationship Between Slavery and Industrial Innovation

The above discussion leads to three testable hypotheses about the relationship between slavery and innovation. First, the negative link between slavery and innovation would have emerged after Reconstruction. As described in Section 2.1, historical slave concentration induced more intensive implementation of post-Reconstruction policies, which contributed to greater control over Black workers. Considering the potential effect of post-Reconstruction institutions on innovation environment, this suggests that the legacy of slavery on innovation became evident after Reconstruction.[7]

Also, we expect the relationship between slavery and innovation to be weaker in agriculture. Given that slaves had been primarily exploited for agricultural production,

of tractors, and Hornbeck and Naidu (2014) document a positive impact of Black out-migration due to flood on modernization of agricultural production.

[7]The interaction between slavery and post-Reconstruction policies may have created labor market conditions that were less attractive to potential immigrants. Considering that our sample period coincides with the period of the Age of Mass Migration, it needs to be verified that differential trends in immigration do not confound the suggested mechanism. In this regard, Appendix A.4 shows that our estimates are not sensitive to controlling for the proportion of the foreign born and its skill composition.

emancipation was a significant shock to the industrial labor market.[8] For example, Terrill et al. (1976) report that labor shortages for the southern textile industry was in general resolved after the Civil War, and Hutchinson and Margo (2006) show a significant decline in capital-labor ratios in southern manufacturing following the War. This fundamental shift in the labor market suggests that consequences of the relevant policy changes would have been particularly noticeable in the industrial sector. In contrast, the revival of the extractive labor market would have been less impactful in agriculture, which had long depended on the forced labor system.[9]

Finally, the proposed mechanism implies a negative link between slavery and the return to skills after Reconstruction. We suggested two potential channels between post-Reconstruction policies and innovation: labor costs and institutional quality. Despite differences in their details, both channels rely on technical changes biased toward unskilled labor. Since this indicates a relative decline in the demand for skilled labor, the return to skills would be expected to decrease after Reconstruction with previous slave concentration. In this regard, we predict that the shadow of slavery on innovation would have been less pronounced in high-skill industries because of the difficulty in shifting production technologies biased toward the use of unskilled labor.

3 The Legacy of Slavery on Industrial Innovation

This section shows that higher prevalence of slavery led to a relative decline in industrial innovation after Reconstruction. Consistent with our predictions, this relationship was pronounced only in the industrial sector, with a greater impact on low-skill industries. Section 3.1 describes the data sources, and Section 3.2 illustrates our estimation strategy. In Section 3.3, we provide the estimation results.

3.1 Patent Data

To measure the extent of innovation across counties, we employ the HistPat database that provides the geography of patents granted by the USPTO from 1790 to 1975 (Petralia et al., 2016). The data contains detailed information about the location (county FIPS code) of inventors and assignees, the year the patent was published, and the patent publication

[8] Starobin (1970) estimates that about 5% of the total slave population in the 1850s worked in industry.

[9] Obviously, the abolition of slavery had profound effects on southern agriculture such as changes in contractual mix (Alston and Higgs, 1982), a decline in farm productivity (Margo, 2002), or shift in agricultural legal system (Woodman, 1979). However, this study focuses on the consequences of the rise of a hierarchical labor market that was not available in the past, which were more salient in the industrial sector.

number.

The patent data is complemented by the CPC codes, a patent classification system collected from Google Patents based on the patent publication number. To match the patent classification with the Census industry codes, we first use a CPC to NAICS (the North American Industry Classification System) concordance (Lybbert and Zolas, 2014) and then create a crosswalk from NAICS to the industry classification in the historical US census data (IND1950). The year of patent application is identified using the patent publication number from the PATSTAT database (European Patent Office, 2017).

Based on the above dataset, we construct the log number of patents per thousand population at the county-level. The number of total patents are normalized by county population, and the size of the relevant labor force serves as a denominator for patents in the corresponding sectors or industries. The size of the relevant labor force is computed from the complete-count census data (Ruggles et al., 2021).

Table 1: PATENT INTENSITY BEFORE THE CIVIL WAR BY THE PREVALENCE OF SLAVERY

	High slave prop.	Low slave prop.	Difference	Correlation with slave prop.	
	(1)	(2)	(3)	(4)	(5)
Patents	1.669	1.498	0.170	0.522	-0.714
			(0.374)	(0.822)	(2.222)
				[0.891]	[2.178]
Patents per population	0.113	0.089	0.024	0.062	0.071
			(0.014)	(0.031)	(0.036)
				[0.035]	[0.041]
Manufacturing patents per worker	11.913	12.257	-0.344	8.921	-0.183
			(4.269)	(15.902)	(18.331)
				[15.205]	[16.824]
State fixed effects				No	Yes
Number of counties	531	532	1,063	1,063	1,063

Notes: Columns (1) and (2) show the counties with higher and lower prevalence of slavery, based on the median of the slave-to-population ratio in 1860. Their differences are reported in Column (3) with standard errors in parentheses. In Columns (4) and (5), we report the estimates from the regression of the patent variables on the slave-to-population ratio. The standard errors in parentheses are clustered at the county level, and Conley standard errors with a 100km cutoff are shown in brackets.

Table 1 presents the average number of patents between 1851 and 1860 across counties.

To explore whether patenting varied with slavery before the Civil War, we split the sample counties into two groups based on the median of the slave-to-population ratios in 1860. As shown in Columns (1) and (2), the number of patents does not show a significant difference between the two groups, which is further supported by the differences and their standard errors in Column (3). Columns (4) and (5) regress the patent variables on the slave-to-population ratio. In both cases with and without the state fixed effects, the estimated coefficients of the proportion enslaved are not significant. This suggests that patent activities were not closely linked to the local prevalence of slavery before the Civil War. In Appendix D, we further substantiate that our baseline specification satisfies the parallel trend assumption.

3.2 Estimation Strategy

This study uses a continuous difference-in-differences model to evaluate the suggested hypotheses. While this approach is suited to investigate structural breaks in the relationship between slavery and innovation, the endogenous nature of slavery may complicate interpretation of the results. Two address this issue, we suggest an IV strategy that exploits agro-climatic variation in the production of the slave crops. Section 3.2.1 describes the baseline estimating equations, and Section 3.2.2 introduces the IV strategy.

3.2.1 Estimating Equations

The hypothesis of this study consists of two propositions: first, the historical prevalence of slavery had negative effects on industrial innovation; second, this relationship emerged after Reconstruction following institutional changes in labor market conditions.

We examine these arguments using three equations, which share a common structure but with different sample and treatment periods. Equation 1 shows the basic form of our specifications. The outcome variable Y_{ct} is the log number of patents per thousand population in year t in county c, where the relevant population depends on the sector or industry of patents. Slave_c indicates the slave-to-population ratio of county c in 1860. The variable of interest is $\text{Slave}_c \times \text{Post}$, which is the interaction term between historical slave concentration and the post-treatment dummy. Conditional on the county fixed effects (δ_c) and state-year fixed effects (δ_{st}), $\text{Slave}_c \times \text{Post}$ evaluates differential trends in innovation based upon the local history of slavery.

$$Y_{ct} = \alpha + \beta \ \text{Slave}_c \times \text{Post}_t + \delta_c + \delta_{st} + \epsilon_{ct} \tag{1}$$

Our empirical estimation differentiates the sample period and the post-treatment dummy in three ways. The first specification in Equation 2 is estimated from 1850 to 1900, with the post-Civil War dummy equal to 1 for years 1870 and later.[10] $\text{Slave}_c \times$Post-Civil War estimates the change in the trend of patents after the Civil War, in relation to the historical prevalence of slavery.

$$Y_{ct} = \alpha + \beta \text{ Slave}_c \times \text{Post-Civil War}_t + \delta_c + \delta_{st} + \epsilon_{ct} \quad \text{for} \quad 1850 \leq t \leq 1900 \tag{2}$$

While Equation 2 assesses the legacy of slavery, we need to verify whether this relationship emerged immediately after the Civil War or became evident after Reconstruction. We consider two more specifications in answering this question. First, we estimate Equation 3 as a falsification test. All the other settings are the same as in Equation 2, but its sample period is restricted to 1850-1880. Given that the post-Reconstruction period is excluded from the estimation, comparable results from Equations 2 and 3 would imply that the effects of slavery on innovation emerged shortly after the Civil War. In contrast, if the results of Equation 2 and 3 are not consistent, it suggests that the differential trends in innovation did not become evident until the end of Reconstruction.

$$Y_{ct} = \alpha + \beta \text{ Slave}_c \times \text{Post-Civil War}_t + \delta_c + \delta_{st} + \epsilon_{ct} \quad \text{for} \quad 1850 \leq t \leq 1880 \tag{3}$$

In addition to the falsification test, we estimate Equation 4 to corroborate the post-Reconstruction effect. The sample period is restricted to 1870-1900 (the postbellum era), and the post-Reconstruction dummy takes value 1 for years 1890 and 1900. If there was a structural break in the relationship between slavery and innovation after Reconstruction, the estimated coefficients of $\text{Slave}_c \times$Post-Civil War would be negative.

$$Y_{ct} = \alpha + \beta \text{ Slave}_c \times \text{Post-Reconstruction}_t + \delta_c + \delta_{st} + \epsilon_{ct} \quad \text{for} \quad 1870 \leq t \leq 1900 \tag{4}$$

It should be noted that our findings are not sensitive to different specifications. Appendix A reports the robustness to three alternative estimation strategies. In Appendix A.1, we incorporate the separate difference-in-differences equations into a single specification. Appendix A.2 estimates the time-varying relationship between slavery and innovation over decades, and Appendix A.3 reproduces the baseline estimates using an extended sample period that ends in 1940.

[10]Section 3 restricts the sample period to 1850-1900 in consideration of the balance between the pre- and post-treatment period. In Appendix A.3, we show that the expansion of the sample period does not alter our findings.

3.2.2 Instrumental Variable Strategy

A key concern with the estimation is that the local prevalence of slavery was not an exogenous characteristic. If historical slave concentration was associated with certain local conditions that had a direct influence on innovation, the estimates from the difference-in-differences model would be biased.

To address the potential endogeneity of slavery, this study employs an IV strategy suggested by (Jung, 2021) that hinges on the agro-climatic variation in crop production. Given that slavery in the South was exploited primarily for producing cotton, tobacco, sugarcane, and rice, specialization in these four crops may be a good predictor of the prevalence of slavery. However, considering that crop mix is affected by various local characteristics, we need to differentiate exogenous and endogenous variations in the production of the slave crops to construct a valid IV.

This study exploits agro-climatic conditions for estimating the exogenous variation in crop mix. Following Fiszbein (2022), we use a FML framework to identify the variation in crop mix that is attributable to the distribution of climate-based crop suitability. The FML model is shown in Equation 5. The outcome variable θ_{ic} denotes the acreage share of crop i in county c, which is computed from the 1860 Census of Agriculture.[11] Π_c is the vector of crop-specific suitability of county c, which is measured by the maximum attainable yields obtained from FAO-GAEZ (IIASA, 2012).[12]

$$\theta_{ic} = \frac{e^{\beta_i \Pi_c}}{1 + \sum_{j=1}^{I-1} e^{\beta_j \Pi_c}} + \xi_{ic} \tag{5}$$

Equation 5 splits the the acreage share of crop i into two components. The first is the agro-climatic variation, which is a function of the vector of crop suitability (Π_c) and crop-level market conditions (β).[13] The second is the error term ξ_{ic}, which represents the potentially endogenous variation in the crop share, affected by other local characteristics such as socioeconomic or cultural conditions.

The climate-based variation in the acreage share $\hat{\theta}_{ic}$ is defined as the potential share of crop i in county c.[14] After estimating Equation 5 for the crops reported in the 1860

[11]The amount of production reported in the Census is converted into acreage based on the figures from Wright (1899). More details can be found in Jung (2021).

[12]We use the GAEZ model of crop suitability under rain-fed and intermediate input conditions, which match the agricultural environment in the late 19th century in the South. Using alternative models of crop suitability does not alter our findings.

[13]Crop prices can be a typical example of β. Conditional on the distribution of crop suitability, a higher relative price of crop i would increase its production. Since β_is are identical across counties, they do not reflect any county-level endogeneity.

[14]More precisely, it is the optimal probability of growing crop i in county c for profit maximization,

Census of Agriculture, we use the sum of the potential shares of cotton, rice, tobacco, and sugarcane as an IV for the 1860 slave-to-population ratio. That is, $\text{Slave}_c \times \text{Post}_t$ is instrumented by $\text{IV}_c \times \text{Post}_t$ for each corresponding post-treatment dummy, where IV_c is the potential share of the slave crops in 1859. Figure 1 illustrates the significant correlation between the IV and the slave-to-population ratio, which supports the relevance of the IV strategy. However, the exclusion restriction might still remain a concern. If agro-climatic conditions had direct effects on the dynamics of innovation, the OLS estimates would lead to a spurious relationship between slavery and patents. To address this issue, Appendix C suggests a placebo test using the potential share of the slave crops in non-southern counties.

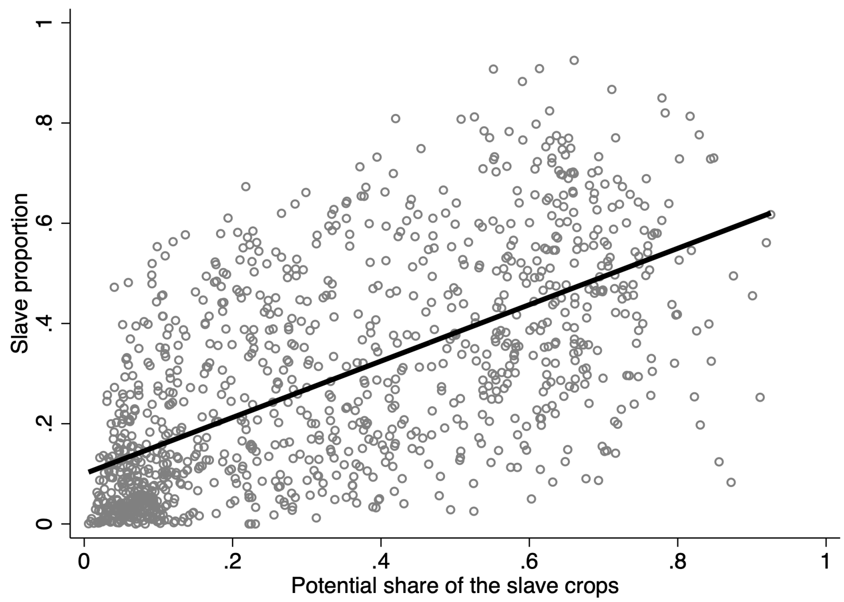


Figure 1: The correlation between the potential share of the slave crops and slave-to-population ratio

Notes: This plot shows the county-level correlation between the potential share of the slave crops in 1859 and the slave-to-population ratio in 1860.

3.3 Slavery and Patents: Differential Trends after Reconstruction

3.3.1 Overall Relationship

This section examines the structural break in the relationship between slavery and patents after Reconstruction. Table 2 presents the estimation results for the three specifications discussed in Section 3.2. Columns (1) and (2) use the baseline sample period that ends in

conditional on the distribution of crop-specific suitability. Jung (2020) provides a theoretical framework that links the individual crop choice to the county-level acreage share.

1900 (1850-1900 for Panel A and 1870-1900 for Panel C), and Columns (3) and (4) extend the estimation up to 1940. In the remaining tables, we focus on the baseline sample period and list the estimates from the extended period in Appendix A.3.

Table 2: THE CHANGING RELATIONSHIP BETWEEN SLAVERY AND PATENTS

Dependent variable: log number of patent applications per thousand population				
	Baseline sample period		Extended sample period	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
A. post-Civil War				
Slave proportion	-0.054	-0.125	-0.120	-0.155
× post-Civil War	(0.033)	(0.069)	(0.035)	(0.073)
	[0.028]	[0.059]	[0.029]	[0.058]
Observations	5,526	5,526	9,210	9,210
R-squared	0.716		0.716	
Kleibergen–Paap F-statistic		264.89		264.89
B. post-Civil War: restricted until Reconstruction				
Slave proportion	-0.010	-0.016	-0.010	-0.016
× Reconstruction	(0.031)	(0.063)	(0.031)	(0.063)
	[0.025]	[0.056]	[0.025]	[0.056]
Observations	3,684	3,684	3,684	3,684
R-squared	0.675		0.675	
Kleibergen–Paap F-statistic		264.89		264.89
C. post-Reconstruction				
Slave proportion	-0.088	-0.218	-0.151	-0.193
× post-Reconstruction	(0.035)	(0.084)	(0.033)	(0.073)
	[0.027]	[0.062]	[0.022]	[0.047]
Observations	3,684	3,684	9,210	9,210
R-squared	0.784		0.717	
Kleibergen–Paap F-statistic		264.89		264.89
County fixed effects	Yes	Yes	Yes	Yes
State-year fixed effects	Yes	Yes	Yes	Yes

Notes: The outcome variable is the log number of patents per thousand population. On a 10-year basis, the baseline sample period is 1850-1900 (Panel A) and 1870-1900 (Panel C), and the extended sample period is 1850-1940 (Panel A) and 1870-1940 (Panel C). Panel B is estimated from 1850 to 1880 for all columns. Standard errors in parentheses are clustered at the county level, and Conley standard errors with a cutoff of 100km are shown in brackets.

In Panel A, we consider the years after the Civil War as the post-treatment period. The results indicate a relative decline in patents in slave-intensive counties after the Civil War. Both the OLS and IV estimates are negative, but the effect size is larger in the IV specification. According to the IV estimate in Column (2), a 1 percentage point (pp) higher slave-to-population ratio was associated with a 0.12% decrease in patents in the postbellum period.

However, the decline in innovation after the Civil War was not evident during Reconstruction. Panel B restricts the estimation up to 1880, three years after the end of Reconstruction, and this makes the negative estimates disappear. Given that the relationship vanishes when the post-Reconstruction period is excluded from the estimation, we can infer that the decline in patents in relation to slavery was not just a postbellum phenomenon, but involves a structural break after the Reconstruction period. Evidence in Panel C corroborates the transition in the post-Reconstruction period. By restricting the sample period to the postbellum era, we examine the changing relationship between slavery and patents as of the end of Reconstruction. The negative estimates confirm that the adverse effects of historical slave concentration on innovation emerged after Reconstruction. Overall, evidence from the three specifications substantiate that the post-Reconstruction period was a critical juncture in the legacy of slavery on innovation.

3.3.2 Heterogeneity between Agriculture and Manufacturing

Beyond reduced innovation after Reconstruction, we expect heterogeneity between the agricultural and industrial sectors. Given that our hypothesis hinges on the argument that the shift in labor market conditions after Reconstruction fostered unskill-biased technical change, the effects of unskill-biased technical change is expected to be more evident in industry than in agriculture, which had long been dependent on the forced labor system.

Table 3 documents sectoral differences in the relationship between slavery and innovation. The classification of manufacturing and agricultural patents follows the CPC codes. To estimate the effects conditional on sectoral size, we use the number of patents per thousand workers in each sector as outcome variables.[15] As shown in Columns (1) and (2), the results from manufacturing patents are consistent with the baseline estimates. Panel A indicates a relative decline in industrial patents in slave-intensive counties after the Civil War, but Panels B and C substantiate that this relationship emerged only after the Reconstruction period. Moreover, the effect sizes are larger than the estimates using total patents, which support a more pronounced impact in the industrial sector.

In contrast, the estimates using agricultural patents are not comparable. Both the OLS

[15]The number of workers in manufacturing and agriculture is obtained from the complete-count censuses.

and IV results in Panel A do not support a postbellum decline in agricultural patents in relation to slavery. The OLS estimate in Panel C suggests a negative association between slavery and agricultural patents after Reconstruction, but the IV strategy negates this correlation. Overall, the estimates suggest a more pronounced impact of slavery on manufacturing patents, which substantiates a distinctive relationship between slavery and industrial innovation.

Table 3: THE CHANGING RELATIONSHIP BETWEEN SLAVERY AND PATENTS BY SECTOR

Dependent variable: log number of patent applications per thousand workers				
	Manufacturing		Agriculture	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
A. post-Civil War				
Slave proportion	-0.149	-0.984	-0.069	0.129
× post-Civil War	(0.239)	(0.492)	(0.055)	(0.089)
	[0.210]	[0.471]	[0.039]	[0.066]
Observations	5,286	5,286	5,439	5,439
R-squared	0.621		0.495	
Kleibergen–Paap F-statistic		247.92		264.67
B. Reconstruction				
Slave proportion	0.170	0.099	0.003	0.099
× Reconstruction	(0.273)	(0.576)	(0.058)	(0.093)
	[0.222]	[0.564]	[0.041]	[0.068]
Observations	3,448	3,448	3,597	3,597
R-squared	0.611		0.495	
Kleibergen–Paap F-statistic		252.32		264.69
C. post-Reconstruction				
Slave proportion	-0.842	-2.247	-0.133	0.065
× post-Reconstruction	(0.285)	(0.560)	(0.051)	(0.109)
	[0.234]	[0.531]	[0.041]	[0.083]
Observations	3,605	3,605	3,684	3,684
R-squared	0.608		0.583	
Kleibergen–Paap F-statistic		275.18		264.89
County fixed effects	Yes	Yes	Yes	Yes
State-year fixed effects	Yes	Yes	Yes	Yes

Notes: The outcome variable is the log number of patents per thousand workers in each sector. Standard errors in parentheses are clustered at the county level, and Conley standard errors with a cutoff of 100km are shown in brackets.

3.3.3 Heterogeneity between Low- and High-skill Industries

Even within the industrial sector, the legacy of slavery on innovation varied across industries. As discussed in Section 2.3, we hypothesize that the changes in production technology would have been more evident in low-skill industries, which were more suited to institutional changes promoting the use of unskilled labor. If this proposition holds, the decline in patents after Reconstruction would be less pronounced in high-skill industries.

To evaluate this premise, we classify manufacturing patents that are related to low- and high-skill industries, respectively. Classification of industry skill level relies on the composition of occupational skill levels, which are proxied by the EDSCOR50 variable in the census, indicating the percentage of workers in each occupational category with at least one year of college education. Using the industry-level average of EDSCOR50 as an index of industry skill level, we use the median of the index values as a threshold for low- and high-skill industries. To match the skill classification with the patent data, we use a CPC to NAICS concordance (Lybbert and Zolas, 2014) and create a crosswalk from NAICS to IND1950.

Table 4 summarizes the heterogeneity within the industrial sector. The estimates from total manufacturing patents are listed in Columns (1) and (2) for comparison, and Columns (3) and (4) show the results using patents related to low-skill industries. The relationship between slavery and low-skill patents is consistent with our baseline findings. Historical slave concentration led to a decrease in patents for low-skill industries after the Civil War (Panel A), but this was not a postbellum shift (Panel B) but rather a post-Reconstruction phenomenon (Panel C). On the other hand, Columns (5) and (6) show that high-skill patents did not experience a significant change in their relationship with slavery. Although the IV estimates in Panels A and C are negative, they are not statistically significant with smaller magnitudes.

Table 4: THE CHANGING RELATIONSHIP BETWEEN SLAVERY AND MANUFACTURING PATENTS

Dependent variable: log number of patents per thousand workers						
	Total manufacturing		Low-skill industries		High-skill industries	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
A. post-Civil War						
Slave proportion	-0.149	-0.984	-0.246	-1.491	0.219	-0.220
× post-Civil War	(0.239)	(0.492)	(0.209)	(0.439)	(0.138)	(0.300)
	[0.210]	[0.471]	[0.185]	[0.456]	[0.140]	[0.305]
Observations	5,286	5,286	5,267	5,267	5,206	5,206
R-squared	0.621		0.594		0.405	
Kleibergen–Paap F-statistic		247.92		248.12		239.62
B. Reconstruction						
Slave proportion	0.170	0.099	0.031	-0.688	0.263	0.019
× Reconstruction	(0.273)	(0.576)	(0.228)	(0.440)	(0.156)	(0.342)
	[0.222]	[0.564]	[0.192]	[0.397]	[0.116]	[0.319]
Observations	3,448	3,448	3,433	3,433	3,379	3,379
R-squared	0.611		0.557		0.406	
Kleibergen–Paap F-statistic		252.32		253.42		240.90
C. post-Reconstruction						
Slave proportion	-0.842	-2.247	-0.688	-1.639	-0.182	-0.536
× post-Reconstruction	(0.285)	(0.560)	(0.244)	(0.517)	(0.212)	(0.461)
	[0.234]	[0.531]	[0.189]	[0.472]	[0.200]	[0.354]
Observations	3,605	3,605	3,596	3,596	3,560	3,560
R-squared	0.608		0.617		0.436	
Kleibergen–Paap F-statistic		275.18		274.85		269.50
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
State-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The outcome variable is the log numbers of patents per thousand workers. Classification of low- and high-skill industries is based upon the industry-level average of the EDSCOR50 variable, which indicates the percentage of workers in each occupational category with at least one year of college education. Standard errors in parentheses are clustered at the county level, and Conley standard errors with a cutoff of 100km are shown in brackets.

4 Mechanism: Decline in Demand for Skills

This study hypothesizes that the legacy of slavery on industrial innovation emerged through post-Reconstruction policies that facilitated intensive use of unskilled labor.[16] Evidence in Section 3 coincides with this proposition in its timing and heterogeneity across industries. To verify the mechanism further, this section explores the dynamics of the demand for skills. Using the return to literacy as a proxy for skill demands, we provide direct evidence of the impact of slavery on unskill-biased technical change in the industrial sector.

4.1 Estimation Using the Return to Literacy

To investigate the dynamic relationship between slavery and industrial production technology, we need to measure skill demands over time. The return to education can be a valid proxy in two senses. First, conditional on the supply of educated workers, lower demand for skills would reduce the return to education. Second, it can be estimated over time in a consistent manner using the census data. On this basis, many studies have used different forms of the return to education to track changes in the skill premium (Card and Lemieux, 2001; Goldin and Katz, 2010; Autor, 2014).

However, since education level is not available in the census data during our sample period, this section uses the return to literacy as an alternative measure of skill demand. We investigate if the historical prevalence of slavery induced a decline in the return to literacy in manufacturing and whether this relationship emerged after Reconstruction.

Equation 6 estimates the dynamic relationship between slavery and the return to literacy for manufacturing workers using the complete-count census data.[17] Slave_c is the 1860 slave-to-population ratio of county c, and Literacy_{ict} is the literacy dummy equal to 1 if individual i in county c is able to read and write in year t. The outcome variable Skilled Occ_{ict} indicates the status of having a skilled occupation. Occupational skill level is classified based on the EDSCOR50 variable, which represents the educational level of workers in each occupational category.[18] If EDSCOR50 of an occupation is larger than that of "Laborers", it is defined as a skilled occupation. Taking into account the relevance

[16] In Section 2, we suggested relative input costs and institutional environment as potential factors in the shift in production technology. Despite the difference in their underlying motivations, both approaches are identical in terms of the decline in demand for skills.

[17] Equation 6 is estimated using the OLS method. While logit and probit regressions provide comparable results, they are not preferred due to the incidental parameter problem.

[18] As mentioned in Section 3.3, EDSCOR50 indicates the percentage of workers who had completed at least one year of college.

of literacy in occupational choice, occupations whose EDSCOR50 are larger than that of "Craftsmen and kindred workers" are excluded from our analyses.[19]

The variable of interest is $\text{Slave}_c \times \text{Literacy}_{ict}$. By estimating the time-varying coefficients of the interaction between individual literacy and historical slave concentration, we explore how the effectiveness of literacy in the labor market changed in relation to the local history of slavery. For example, if the value of β_t is negative, it suggests that literate workers in counties with higher slave-to-population ratios in 1860 were less likely to have skilled occupations in year t. The sample consists only of White workers for a proper estimation of the return to literacy in manufacturing. The vast majority of freed Blacks in manufacturing were employed in unskilled jobs, and their occupational status was contingent on various factors other than literacy, such as discrimination or inexperience in the industrial sector. Thus, including Black workers may falsely cause a structural break in the the return to literacy after the Civil War, even without a significant change in production technologies.

$$\text{Skilled Occ}_{ict} = \Sigma_t \beta_t \text{ Slave}_c \times \text{Literacy}_{ict} + \Sigma_t \gamma_t \text{Literacy}_{ict} + \lambda' \boldsymbol{X}_{ict} + \delta_{IND} + \delta_{ct} + \epsilon_{ict} \quad (6)$$

The return to literacy is estimated conditional on a battery of controls. First, the time-varying coefficients of the literacy dummy (γ_t) reflect periodic changes in the demand and supply of literate workers in the South. δ_{ct} indicates county-year fixed effects, which absorb unobserved county-specific factors across time.[20] X_{ict} is a vector of individual controls including age, age-squared, sex, nativity, rural-urban status, and household head status. We also control for industry fixed effects (δ_{IND}) considering the potential association between the local history of slavery and industrial structure.[21]

4.2 The Relationship between Slavery and the Return to Literacy

Figure 2 illustrates the changing relationship between slavery and the return to literacy in manufacturing.[22] The pattern is consistent with the suggested mechanism. The small and insignificant estimates until 1880 suggests that slavery did not have significant effects

[19] EDSCOR50 of "Craftsmen and kindred workers" is 6.4, which corresponds to the third quartile of the distribution of EDSCOR50 in 1880. The results are robust to different cutoff values or using all occupations.

[20] For instance, contemporary demographic conditions or industrial structures at the county-level are absorbed by the county-year fixed effects.

[21] For example, cotton specialization based on slave labor may have fostered the growth of textile industries. If their low-skill intensity reduced skill demands of local manufacturing, it could be an alternative channel for the decline in the return to literacy.

[22] The corresponding Table for the figures can be found in Appendix G.

on skill demands in manufacturing before the end of Reconstruction. However, the estimates decline to negative values in the subsequent period. This indicates that literate manufacturing workers in counties with higher slave proportions became less likely to have skilled occupations after Reconstruction. Given that historical slave concentration was not a factor that increased the supply of skilled workers, this is interpreted as a reduced demand for skills in the post-Reconstruction period.

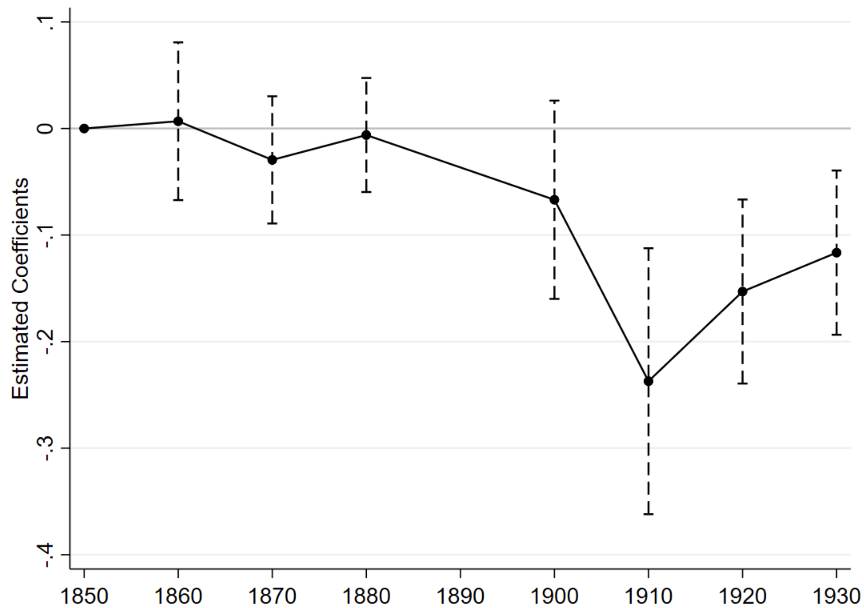
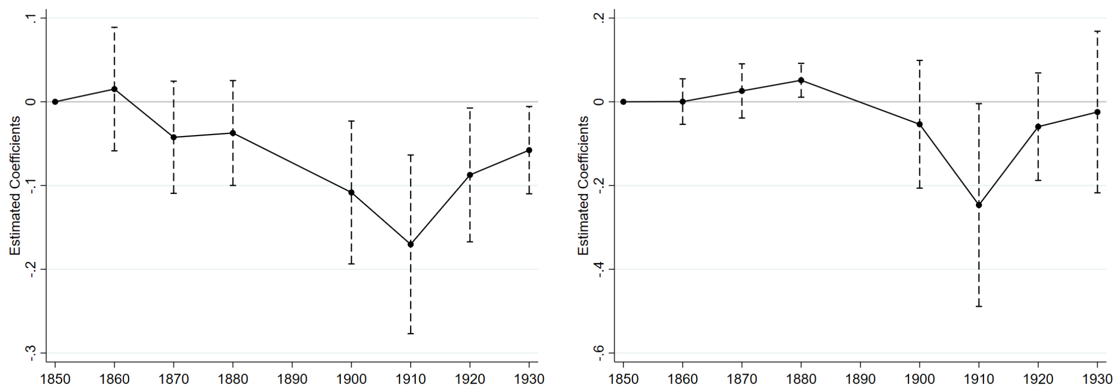


Figure 2: SLAVERY AND THE RETURN TO LITERACY IN MANUFACTURING OVER TIME

Notes: The figure shows the estimated coefficients and 95% confidence intervals from Equation 6. The outcome variable is the status of having skilled occupations, and the variable of interest is an interaction term between the slave-to-population ratio in 1860 and individual literacy in year t. The results are conditional on county-year fixed effects, industry fixed effects, and individual controls. Individual controls include age, age squared, urban residence, nativity, gender, and race. Standard errors are clustered at the county-level.

Furthermore, the decline in the return to literacy was more pronounced in low-skill industries. Figure 3 shows the relationship between slavery and the return to literacy estimated for low- and high-skill industries, respectively. Industry skill level is proxied by the average value of the EDSCOR50 variable of industry workers, as discussed in Section 3.3. The estimates from low-skill industries in Figure 3-(a) are consistent with the results from total manufacturing. The return to literacy does not vary with slavery until 1880, but the coefficients decline significantly in the post-Reconstruction period. In contrast, the coefficients are relatively stable in the estimation using high-skill industries. Despite the negative coefficient in 1910, the estimates are not significantly different from zero in the other period. This difference supports the hypothesis that the effect of slavery on unskill-biased technical change after Reconstruction would have been more evident in low-skill industries, based upon their suitability for technological adjustment.



(a) Low-skill industries (b) High-skill industries

Figure 3: SLAVERY AND THE RETURN TO LITERACY IN MANUFACTURING: LOW- AND HIGH-SKILL INDUSTRIES

Notes: The figures show the estimated returns to literacy in low- and high-skill industries, respectively. Industry skill level is proxied by the industry-level average value of the EDSCOR50 variable, and their median is used as a cutoff for low-skill industries.

A potential concern with the regressions over a decade is that the IV strategy is not applicable. Despite the county-year fixed effects, which absorb unobserved dynamic county factors, differential effects of alternative local traits on the return to literacy might still affect the results. In particular, given that slavery was more prevalent in less industrialized regions, initial differences in industrial development may be a source of potential bias. If post-Reconstruction policies promoted skill-biased technical change depending on the initial industrial structures, it may falsely lead to a negative relationship between slavery and the return to literacy after Reconstruction. To address this concern, Appendix B tests the robustness to time-varying effects of additional controls that proxy the initial stages of industrial development.

5 Conclusion

Slavery has left a deep mark on the American South. By focusing on the dynamics of innovation, this study reveals a novel aspect of the legacy of slavery. Drawing on the recent findings that historical slave concentration led to stricter implementation of post-Reconstruction policies that reinforced hierarchy in the labor market, we hypothesize that a negative link between slavery and innovation emerged after Reconstruction through unskill-biased technical change.

We evaluate this hypothesis using a continuous difference-in-differences model. To address the potential endogeneity of slavery, historical slave concentration is instrumented by the potential share of the slave crops, which indicates the agro-climatic variation in the acreage share of cotton, tobacco, rice, and sugarcane in 1859. The evidence supports our proposition. We find a negative relationship between the historical prevalence of slavery and the number of patents, which became evident from the post-Reconstruction period. This relationship was not homogeneous throughout the economy. Contrary to the significant reduction in industrial innovation, the effect of slavery was not noticeable in agriculture, which has a long history of unskill-biased production technology based on slavery.

Even within the industrial sector, the post-Reconstruction effect of slavery on patents was more pronounced in low-skill industries. This supports our hypothesis that unskill-biased technical change was a less workable alternative in high-skill industries. To validate the suggested mechanism further, we examine the relationship between slavery and the demand for skills over time. Skill demands are proxied by the return to literacy, which indicates the likelihood of literate workers having skilled occupations. Our evidence illustrates that the relationship between slavery and skill demand turned negative from the post-Reconstruction period. Moreover, the decline in skill demand was more evident in low-skill industries, which corroborates the findings from the patent data.

Considering the essential role of innovation in economic development, our findings contribute to understanding the fundamental forces of the legacy of slavery. In particular, the significance of post-Reconstruction as a critical juncture suggests that the lasting impact of slavery is not merely an extension of the "peculiar" institution, but rather a product of its interplay with different institutional factors. Beyond American economic history, studying interaction among various institutions may be a promising approach to elucidate the mechanism of the institutional roots of long-run development.

References

Aaronson, D. and B. J. Phelan (2019): "Wage shocks and the technological substitution of low-wage jobs," *The Economic Journal*, 129, 1–34.

Acemoglu, D. (1998): "Why do new technologies complement skills? Directed technical change and wage inequality," *The quarterly journal of economics*, 113, 1055–1089.

——— (2002): "Directed technical change," *The review of economic studies*, 69, 781–809.

——— (2010): "When does labor scarcity encourage innovation?" *Journal of Political Economy*, 118, 1037–1078.

Acemoglu, D., S. Johnson, and J. A. Robinson (2001): "The colonial origins of comparative development: An empirical investigation," *American economic review*, 91, 1369–1401.

Acemoglu, D., J. Moscona, and J. A. Robinson (2016): "State capacity and American technology: evidence from the nineteenth century," *American Economic Review*, 106, 61–67.

Acemoglu, D. and P. Restrepo (2022): "Demographics and automation," *The Review of Economic Studies*, 89, 1–44.

Acemoglu, D. and J. Robinson (2012a): *Why Nations Fail: the Origins of Power, Prosperity, and Poverty*, New York: Crown Publishers.

Acemoglu, D. and J. A. Robinson (2012b): *Why nations fail: The origins of power, prosperity, and poverty*, Currency.

Ager, P., L. Boustan, and K. Eriksson (2021): "The intergenerational effects of a large wealth shock: white southerners after the Civil War," *American Economic Review*, 111, 3767–94.

Aghion, P. and P. Howitt (1992): "A Model of Growth Through Creative Destruction," *Econometrica*, 323–351.

——— (1996): "Research and development in the growth process," *Journal of Economic Growth*, 1, 49–73.

Akcigit, U. and W. R. Kerr (2018): "Growth through heterogeneous innovations," *Journal of Political Economy*, 126, 1374–1443.

Alston, L. J. and R. Higgs (1982): "Contractual mix in southern agriculture since the Civil War: Facts, hypotheses, and tests," *The Journal of Economic History*, 42, 327–353.

Anderson, J. D. (1988): *The education of Blacks in the South, 1860-1935*, Univ of North Carolina Press.

Andersson, D., M. Karadja, and E. Prawitz (2022): "Mass migration and technological change," *Journal of the European Economic Association*, 20, 1859–1896.

Autor, D. H. (2014): "Skills, education, and the rise of earnings inequality among the "other 99 percent"," *Science*, 344, 843–851.

Banerjee, A. and L. Iyer (2005): "History, institutions, and economic performance: The legacy of colonial land tenure systems in India," *American economic review*, 95, 1190–1213.

Bentley, G. R. (2017): "A History of the Freedmen's Bureau," in *A History of the Freedmen's Bureau*, University of Pennsylvania Press.

Berger, T. (2018): "Places of persistence: Slavery and the geography of intergenerational mobility in the United States," *Demography*, 55, 1547–1565.

Bertocchi, G. and A. Dimico (2014): "Slavery, education, and inequality," *European Economic Review*, 70, 197–209.

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

Cain, L. P. and D. G. Paterson (1981): "Factor biases and technical change in manufacturing: the American system, 1850–1919," *The Journal of Economic History*, 41, 341–360.

Card, D. and T. Lemieux (2001): "Can falling supply explain the rising return to college for younger men? A cohort-based analysis," *The quarterly journal of economics*, 116, 705–746.

Carneiro, P., K. Liu, and K. G. Salvanes (2018): "The supply of skill and endogenous technical change: evidence from a college expansion reform," *Journal of the European Economic Association*.

Carruthers, C. K. and M. H. Wanamaker (2017): "Separate and unequal in the labor market: human capital and the jim crow wage gap," *Journal of Labor Economics*, 35, 655–696.

Clarke, L. W. (2018): *The lineaments of wrath: Race, violent crime, and American culture*, Routledge.

Cohen, W. (1976): "Negro involuntary servitude in the South, 1865-1940: A preliminary analysis," *The Journal of Southern History*, 42, 31–60.

——— (1984): "Black Immobility and Free Labor: The Freedmen's Bureau and the Relocation of Black Labor, 1865-1868," *Civil War History*, 30, 221–234.

Cunningham, D. L. (1991): "Who are to be the electors-a reflection on the history of voter registration in the united states," *Yale L. & Pol'y Rev.*, 9, 370.

Diodato, D., A. Morrison, and S. Petralia (2022): "Migration and invention in the age of mass migration," *Journal of Economic Geography*, 22, 477–498.

Donges, A., J.-M. Meier, and R. C. Silva (2022): "The impact of institutions on innovation," *Management Science*.

Doran, K. and C. Yoon (2020): "Immigration and invention: Evidence from the quota acts," .

Engerman, S. L. and K. L. Sokoloff (1994): "Factor endowments: institutions, and differential paths of growth among new world economies: a view from economic historians of the United States," .

——— (2002): "Factor endowments, inequality, and paths of development among new world economics," .

European Patent Office (2017): "The EPO worldwide patent statistical database. PATSTAT: Version 5.09 [dataset]. 2017 Spring edition," .

Fiszbein, M. (2022): "Agricultural Diversity, Structural Change, and Long-Run Development: Evidence from the United States," *American Economic Journal: Macroeconomics*, 14, 1–43.

Foner, E. (1988): "America's Unfinished Revolution 1863-1877," .

George, P. (2012): *The emergence of industrial America: Strategic factors in American economic growth since 1870*, SUNY Press.

Goldin, C. and L. F. Katz (2010): *The race between education and technology*, harvard university press.

Goldin, C. D. and F. D. Lewis (1975): "The economic cost of the American Civil War: Estimates and implications," *The Journal of Economic History*, 35, 299–326.

Gordon, R. J. (2016): "The rise and fall of American growth," in *The Rise and Fall of American Growth*, Princeton University Press.

Guiso, L., P. Sapienza, and L. Zingales (2016): "Long-term persistence," *Journal of the European Economic Association*, 14, 1401–1436.

Haines, M. R., I. university Consortium for Political, and S. Research (2010): "Historical, Demographic, Economic, and Social Data: The United States, 1790-2002," *Inter-university Consortium for Political and Social Research*.

Hornbeck, R. and S. Naidu (2014): "When the levee breaks: black migration and economic development in the American South," *American Economic Review*, 104, 963–90.

Hunt, J. and M. Gauthier-Loiselle (2010): "How much does immigration boost innovation?" *American Economic Journal: Macroeconomics*, 2, 31–56.

Hutchinson, W. K. and R. A. Margo (2006): "The impact of the Civil War on capital intensity and labor productivity in southern manufacturing," *Explorations in Economic History*, 43, 689–704.

IIASA, F. (2012): "Global Agro-ecological Zones (GAEZ v3. 0)," *IIASA, Laxenburg, Austria and FAO, Rome, Italy*.

James, J. A. (1983): "Structural change in American manufacturing, 1850–1890," *The Journal of Economic History*, 43, 433–459.

Jung, Y. (2020): "The long reach of cotton in the US South: Tenant farming, mechanization, and low-skill manufacturing," *Journal of Development Economics*, 143, 102432.

——— (2021): "Formation of the legacy of slavery: Evidence from the us south," *Available at SSRN 3966791*.

Kerr, S. P., W. Kerr, Ç. Özden, and C. Parsons (2016): "Global talent flows," *Journal of Economic Perspectives*, 30, 83–106.

Khan, Z. and K. L. Sokoloff (2004): "Institutions and democratic invention in 19th-century america: Evidence from" great inventors," 1790-1930," *American Economic Review*, 94, 395–401.

Klette, T. J. and S. Kortum (2004): "Innovating firms and aggregate innovation," *Journal of political economy*, 112, 986–1018.

Kousser, J. M. (1980): "Progressivism-for middle-class whites only: North carolina education, 1880-1910," *The Journal of Southern History*, 46, 169–194.

Lewis, E. (2011): "Immigration, skill mix, and capital skill complementarity," *The Quarterly Journal of Economics*, 126, 1029–1069.

Logan, T. D. (2020): "Do black politicians matter? Evidence from reconstruction," *The Journal of Economic History*, 80, 1–37.

Lybbert, T. J. and N. J. Zolas (2014): "Getting Patents and Economic Data to Speak to Each Other: An 'Algorithmic Links with Probabilities' Approach for Joint Analyses of Patenting and Economic Activity," *Research Policy*, 43, 530–542.

MacLeod, C. (2002): *Inventing the industrial revolution: The English patent system, 1660-1800*, Cambridge University Press.

Manuelli, R. E. and A. Seshadri (2014): "Frictionless technology diffusion: The case of tractors," *American Economic Review*, 104, 1368–91.

Margo, R. A. (1982): "Race differences in public school expenditures: Disfranchisement and school finance in Louisiana, 1890-1910," *Social Science History*, 6, 9–34.

——— (2002): "The North-South wage gap, before and after the Civil War," .

——— (2007): "Race and Schooling in the South, 1880-1950," in *Race and Schooling in the South, 1880-1950*, University of Chicago Press.

Moser, P. and S. San (2020): "Immigration, science, and invention. lessons from the quota acts," .

Naidu, S. (2010): "Recruitment restrictions and labor markets: Evidence from the postbellum US South," *Journal of Labor Economics*, 28, 413–445.

——— (2012): "Suffrage, schooling, and sorting in the post-bellum US South," Tech. rep., National Bureau of Economic Research.

North, D. C. and R. P. Thomas (1970): "An economic theory of the growth of the western world," *The economic history review*, 23, 1–17.

Nunn, N. (2007): "Slavery, inequality, and economic development in the Americas: An examination of the Engerman-Sokoloff hypothesis," .

O'Connell, H. A. (2012): "The impact of slavery on racial inequality in poverty in the contemporary US South," *Social Forces*, 90, 713–734.

Parrotta, P., D. Pozzoli, and M. Pytlikova (2014): "The nexus between labor diversity and firm's innovation," *Journal of Population Economics*, 27, 303–364.

Peri, G., K. Shih, and C. Sparber (2015): "STEM workers, H-1B visas, and productivity in US cities," *Journal of Labor Economics*, 33, S225–S255.

Petralia, S., P.-A. Balland, and D. Rigby (2016): "HistPat Dataset," .

Ransom, R. L. and R. Sutch (2001): *One kind of freedom: The economic consequences of emancipation*, Cambridge University Press.

Richardson, J. M. (1969): "Florida Black Codes," *The Florida historical quarterly*, 47, 365–379.

Roback, J. (1984): "Southern labor law in the Jim Crow era: exploitative or competitive?" *The University of Chicago Law Review*, 51, 1161–1192.

Rogowski, J. C. (2018): "Reconstruction and the state: The political and economic consequences of the freedmen's bureau," in *annual meeting of the American Political Science Association, Boston, MA*.

Ruggles, S., C. A. Fitch, R. Goeken, J. D. Hacker, M. A. Nelson, E. Roberts, M. Schouweiler, and M. Sobek (2021): "IPUMS Ancestry Full Count Data: Version 3.0 [dataset]," *Minneapolis, MN: IPUMS*.

Sacerdote, B. (2005): "Slavery and the intergenerational transmission of human capital," *Review of Economics and Statistics*, 87, 217–234.

San, S. (2022): "Labor Supply and Directed Technical Change: Evidence from the Termination of the Bracero Program in 1964," *American Economic Journal: Applied Economics*.

Sokoloff, K. L. (1984): "Was the transition from the artisanal shop to the nonmechanized factory associated with gains in efficiency?: Evidence from the US Manufacturing censuses of 1820 and 1850," *Explorations in Economic History*, 21, 351–382.

Sokoloff, K. L. and S. L. Engerman (2000): "Institutions, factor endowments, and paths of development in the new world," *Journal of Economic perspectives*, 14, 217–232.

Starobin, R. S. (1970): "The Economics of Industrial Slavery in the Old South," *Business History Review*, 44, 131–174.

Suryanarayan, P. and S. White (2021): "Slavery, reconstruction, and bureaucratic capacity in the American south," *American Political Science Review*, 115, 568–584.

Terrill, T. E., E. Ewing, and P. White (1976): "Eager Hands: Labor for Southern Textiles, 1850-1860," *Journal of Economic History*, 84–99.

Thomas, W. G., R. G. Healey, and I. Cottingham (2017): "Reconstructing African American Mobility after Emancipation, 1865–67," *Social Science History*, 41, 673–704.

Vollrath, D. (2011): "The agricultural basis of comparative development," *Journal of Economic Growth*, 16, 343–370.

Wilson, T. B. (1965): *The black codes of the South*, 6, University of Alabama Press.

Woodman, H. D. (1977): "Sequel to slavery: The new history views the postbellum South," *The Journal of Southern History*, 43, 523–554.

——— (1979): "Post-Civil War Southern Agriculture and the Law," *Agricultural History*, 53, 319–337.

Wright, C. D. (1899): *Hand and Machine Labor...*, Bureau of Labor, United States.

Wright, G. (1987): "The economic revolution in the American South," *Journal of Economic Perspectives*, 1, 161–178.

Wright, G. et al. (1986): *Old South, new South: Revolutions in the southern economy since the Civil War*, Basic Books.

Appendices

A Robustness

This section demonstrates the robustness of our findings to alternative specifications. Appendix A.1 shows that incorporating the pre-Civil War, Reconstruction, and post-Reconstruction periods into a single equation does not change the results. Appendix A.2 finds a similar pattern from time-varying coefficients across decades, and Section A.3 confirms the robustness to the extended sample period.

A.1 Pooled Specification

While the difference-in-differences models in Section 3 are appropriate for analyzing the structural break as of the end of Reconstruction, comparability of the estimates across different sample periods may be a potential concern for the interpretation. In this respect, this section integrates the three separate regressions into a single specification.

$$Y_{ct} = \alpha + \beta \text{ Slave}_c \times \text{Reconstruction}_t + \gamma \text{ Slave}_c \times \text{post-Reconstruction}_t + \delta_c + \delta_{st} + \epsilon_{ct} \quad \text{(A1)}$$

Equation A1 estimates the changing relationship between slavery and patents in the Reconstruction and post-Reconstruction periods. The sample period ranges from 1850 to 1900 on a 10-year basis, and Reconstruction_t and $\text{post-Reconstruction}_t$ are dummy variables that take the value of 1 if year t falls into the Reconstruction (1870, 1880) and post-Reconstruction (1890,1900) periods, respectively. As the antebellum years serve as the reference period, the coefficients β and γ capture the heterogeneous trends in the relationship between slavery and innovation relative to the pre-Civil War period. δ_c and δ_{st} denote county fixed effects and state-year fixed effects.

Table A1 presents the estimation results from Equation A1, which are consistent with the baseline findings. As shown in Columns (1) and (2), the negative link between slavery and industrial innovation is observed exclusively after the Reconstruction period. The estimated coefficients of $\text{Slave}_c \times \text{Reconstruction}_t$ are close to zero both in the OLS and IV specifications, but those of $\text{Slave}_c \times \text{post-Reconstruction}_t$ are significantly negative. The alternative specification also confirms the heterogeneity within manufacturing. As shown in Columns (3) and (4), low-skill industries display the post-Reconstruction decline in patents in relation to historical slave concentration, but the estimates from high-skill industries in Columns (5) and (6) do not show comparable patterns. Overall, the results in Table A1 confirm that our findings are not sensitive to using the whole or split sample periods.

Table A1: SLAVERY AND MANUFACTURING PATENTS: POOLED SPECIFICATION

Dependent variable: log number of patents per thousand workers						
	Total manufacturing		Low-skill industries		High-skill industries	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Slave proportion	0.273	0.155	0.099	-0.654	0.306	0.046
× Reconstruction	(0.270)	(0.568)	(0.223)	(0.437)	(0.155)	(0.338)
	[0.241]	[0.583]	[0.210]	[0.478]	[0.138]	[0.338]
Slave proportion	-0.558	-2.096	-0.581	-2.308	0.136	-0.475
× post-Reconstruction	(0.286)	(0.564)	(0.260)	(0.573)	(0.190)	(0.413)
	[0.244]	[0.524]	[0.211]	[0.579]	[0.202]	[0.375]
Observations	5,286	5,286	5,267	5,267	5,206	5,206
R-squared	0.622		0.595		0.405	
Kleibergen–Paap F-statistic		123.97		124.31		119.81
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
State-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The outcome variables are the log numbers of patents per thousand workers for relevant manufacturing industries. Classification of low- and high-skill industries is based upon the industry-level average of the EDSCOR50 variable, which indicates the percentage of workers in each occupational category with at least one year of college education. Standard errors in parentheses are clustered at the county level, and Conley standard errors with a cutoff of 100km are shown in brackets.

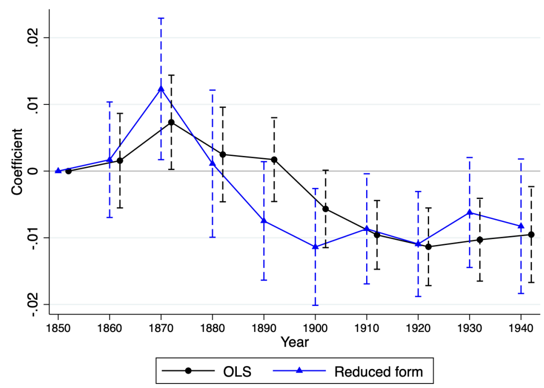
A.2 Time-Varying Coefficients

The difference-in-differences model is preferred as our baseline specification in two respects: first, it is suitable for estimation of the structural break after Reconstruction; second, we can address the potential endogeneity of slavery using the IV strategy. However, despite these advantages, the difference-in-differences estimation may mask the dynamics manifesting within a shorter timeframe.

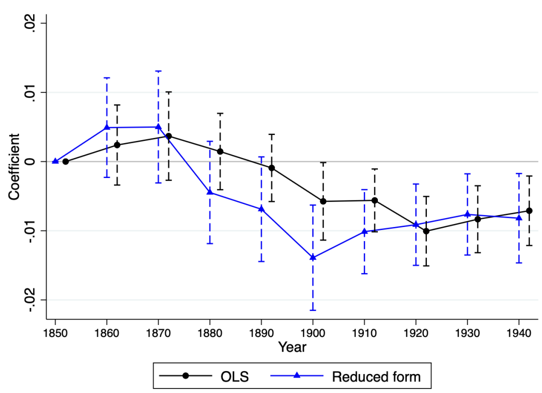
$$Y_{ct} = \alpha + \sum_{t} \beta_t \text{ Slave}_c + \delta_c + \delta_{st} + \epsilon_{ct} \tag{A2}$$

In this context, Equation A2 re-estimates the relationship between slavery and innovation on a 10-year basis, where β_t captures the time-varying effect of slavery on patent activities. As we do not need to balance the number of years between pre- and post-treatment periods, the sample period for Equation A2 is extended from 1850-1900 to 1850-1940.

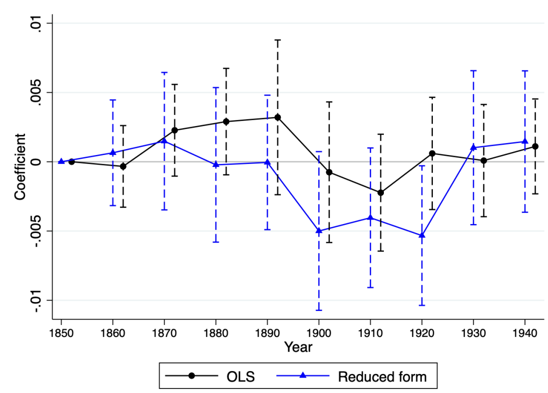
The IV strategy is not applicable to this specification. As an alternative to the 2SLS estimation, we show the reduced form estimates alongside the OLS results using the potential share of the slave crops as an explanatory variable. Considering that the placebo test in Appendix C supports the exclusion restriction of the IV, the reduced form estimates would be informative with respect to causal interpretation.



(a) Total manufacturing



(b) Low-skill industries



(c) High-skill industries

Figure A1: TIME-VARYING RELATIONSHIP BETWEEN SLAVERY AND INDUSTRIAL INNOVATION

Notes: These figures show the regression coefficients and 95% confidence intervals using 1850 as the reference year, conditional on county fixed effects and state-year fixed effects. The confidence intervals are based on Conley standard errors with a cutoff of 100km.

Figure A1 plots the estimates of Equation A2. The black and blue dots indicate the OLS and reduced form estimates with 95% confidence intervals, respectively. The results based on total manufacturing patents in Figure A1-(a) corroborate that the negative link between slavery and industrial innovation emerged after Reconstruction. Both the OLS and reduced form estimates turn negative after Reconstruction, and this relationship persists in the subsequent period. The estimates from low-skill patents exhibit a consistent pattern shown in Figure A1-(b), but Figure A1-(c) illustrates that there was no structural break in the relationship between slavery and high-skill patents. These results confirm that the post-Reconstruction decline in innovation was more pronounced in low-skill industries, which were better suited to unskill-biased technical change.

A.3 Extended Sample Period

To maintain balance in the number of years before and after Reconstruction, our baseline specification restricted the sample period to 1900. While this may raise questions about the persistence of the post-Reconstruction decline in innovation, evidence in Section A.2 supports the long-run negative relationship between slavery and patents beyond 1900. Moreover, the difference-in-differences estimates are robust to extending the sample period. In Table A2, the sample period is extended up to 1940 in Panels A and C. Since the falsification tests in Panel B are estimated up to 1880 by construction, their results are identical to those in Section 3.3. The results confirm the emergence of the negative relationship between slavery and patents after Reconstruction, which was more evident in low-skill industries.

Table A2: SLAVERY AND MANUFACTURING PATENTS: EXTENDED SAMPLE PERIOD 1850-1940

Dependent variable: log number of patents per thousand workers						
	Total manufacturing		Low-skill industries		High-skill industries	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
A. post-Civil War						
Slave proportion	-0.719	-1.552	-0.620	-1.854	0.136	-0.259
× post-Civil War	(0.227)	(0.457)	(0.186)	(0.400)	(0.111)	(0.218)
	[0.206]	[0.431]	[0.172]	[0.447]	[0.106]	[0.239]
Observations	8,868	8,868	8,851	8,851	8,790	8,790
R-squared	0.584		0.566		0.344	
Kleibergen–Paap F-statistic		242.75		242.35		235.86
B. Reconstruction						
Slave proportion	0.170	0.099	0.031	-0.688	0.263	0.019
× Reconstruction	(0.273)	(0.576)	(0.228)	(0.440)	(0.156)	(0.342)
	[0.222]	[0.564]	[0.192]	[0.397]	[0.116]	[0.319]
Observations	3,448	3,448	3,433	3,433	3,379	3,379
R-squared	0.611		0.557		0.406	
Kleibergen–Paap F-statistic		252.32		253.42		240.90
C. post-Reconstruction						
Slave proportion	-1.143	-2.162	-0.880	-1.856	-0.077	-0.392
× post-Reconstruction	(0.217)	(0.436)	(0.163)	(0.379)	(0.126)	(0.274)
	[0.171]	[0.389]	[0.136]	[0.335]	[0.109]	[0.245]
Observations	8,868	8,868	8,851	8,851	8,790	8,790
R-squared	0.586		0.567		0.344	
Kleibergen–Paap F-statistic		261.46		262.27		256.83
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
State-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The outcome variables are the log numbers of patents per thousand workers for relevant manufacturing industries. Classification of low- and high-skill industries is based upon the industry-level average of the EDSCOR50 variable, which indicates the percentage of workers in each occupational category with at least one year of college education. Standard errors in parentheses are clustered at the county level, and Conley standard errors with a cutoff of 100km are shown in brackets.

A.4 Immigration Flows

A growing body of literature focuses on the role of immigrants in innovation, especially in the context of the Age of Mass Migration and the Quota Acts (Diodato, Morrison, and

Petralia, 2022; Doran and Yoon, 2020; Moser and San, 2020). Given that our sample period coincides with the Age of Mass Migration (1850-1913), it should be verified whether differential trends in immigration flows confound the suggested mechanism based on unskill-biased technical change. For example, if the interaction between slavery and post-Reconstruction policies discouraged the inflow of skilled-immigrants due to the extractive labor market conditions, it may have hindered innovation through changes in skill mix (Hunt and Gauthier-Loiselle, 2010; Lewis, 2011; Kerr et al., 2016). Alternatively, considering the recent findings that low-skill immigrants may also promote innovation (Doran and Yoon, 2020; San, 2022; Andersson et al., 2022), immigration volume could have been a separate channel apart from changes in skill mix.

To address this issue, Table A3 tests the robustness our findings to the variables related to immigration, which include the proportion of the foreign-born population and the shares of skilled and literate individuals among foreign-born workers.[23] The estimated relationship between slavery and manufacturing patents is analogous to the baseline results. Even with controls that proxy the volume of immigration and its skill composition, the results illustrate the rise of the negative link between slavery and innovation after Reconstruction, which is evident only with patents related to low-skill industries.

[23] The classification of skilled and unskilled occupations is based upon the EDSCOR50 variable, using the value of "Operative and kindred workers" as a cutoff.

Table A3: SLAVERY AND MANUFACTURING PATENTS: ROBUSTNESS TO IMMIGRATION FLOWS

Dependent variable: log number of patents per thousand workers						
	Total manufacturing		Low-skill industries		High-skill industries	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
A. post-Civil War						
Slave proportion	-0.063	-0.835	-0.183	-1.408	0.237	-0.200
× post-Civil War	(0.236)	(0.499)	(0.208)	(0.445)	(0.138)	(0.303)
	[0.204]	[0.481]	[0.180]	[0.460]	[0.140]	[0.310]
Observations	5,286	5,286	5,267	5,267	5,206	5,206
R-squared	0.623		0.595		0.406	
F-statistic		243.09		243.57		235.53
B. Reconstruction						
Slave proportion	0.265	0.230	0.086	-0.653	0.263	-0.004
× Reconstruction	(0.271)	(0.589)	(0.227)	(0.452)	(0.156)	(0.347)
	[0.215]	[0.581]	[0.186]	[0.405]	[0.115]	[0.325]
Observations	3,448	3,448	3,433	3,433	3,379	3,379
R-squared	0.613		0.559		0.406	
F-statistic		244.70		245.98		234.21
C. post-Reconstruction						
Slave proportion	-0.854	-2.265	-0.699	-1.643	-0.201	-0.534
× post-Reconstruction	(0.286)	(0.560)	(0.244)	(0.516)	(0.214)	(0.459)
	[0.233]	[0.530]	[0.188]	[0.473]	[0.201]	[0.351]
Observations	3,605	3,605	3,596	3,596	3,560	3,560
R-squared	0.608		0.617		0.436	
F-statistic		276.15		275.81		270.38
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
State-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Additional controls						
Foreign born population	Yes	Yes	Yes	Yes	Yes	Yes
Skilled foreign-borns	Yes	Yes	Yes	Yes	Yes	Yes
Literate foreign-borns	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The additional controls include the proportion of the foreign born among the county population, and the shares of skilled and literate individuals among the foreign born, respectively. The foreign born whose EDSCOR50 value is higher than that of "Operative and kindred workers" is classified as skilled. Standard errors in parentheses are clustered at the county level, and Conley standard errors with a cutoff of 100km are shown in brackets.

B Slavery and the Return to Literacy: Robustness

Equation A3 re-estimates the relationship between slavery and the return to literacy with additional county controls. $\boldsymbol{Z}_c$ is the vector of the added controls including the share of farmland, agricultural yield per acre, share of the manufacturing population, average manufacturing wage, and manufacturing value added per worker, which are all measured for 1860. The first three variables represent the initial level of industrialization, and the latter variables relate to industrial productivity at that time. To address their differential effects on skill demands over time, the additional controls are also interacted with individual literacy and have time-varying coefficients.

$$\begin{aligned}\text{Skilled Occ}_{ict} =& \Sigma_t \beta_t \text{Slave}_c \times \text{Literacy}_{ict} + \gamma_t' \boldsymbol{Z}_c \times \text{Literacy}_{ict} + \Sigma_t \eta_t \text{Literacy}_{ict} \\ &+ \lambda' \boldsymbol{X}_{ict} + \delta_{IND} + \delta_{ct} + \epsilon_{ict}\end{aligned} \tag{A3}$$

Figure A2 illustrates the estimation results. Even with the additional county controls, the relationship between slavery and the return to literacy in manufacturing shows a structural break after the Reconstruction period. The coefficients are not significantly different from zero until 1880, but decrease to negative values in the subsequent period. Given that Equation A3 takes into account the time-varying effects of the added controls, the results in Figure A2 substantiate that the post-Reconstruction decline in skill demands is not attributable to the initial industrial structure.

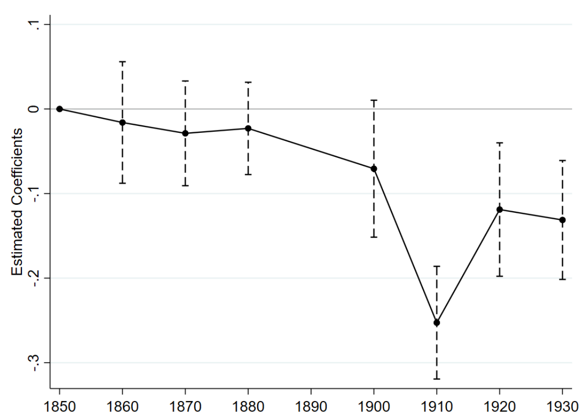
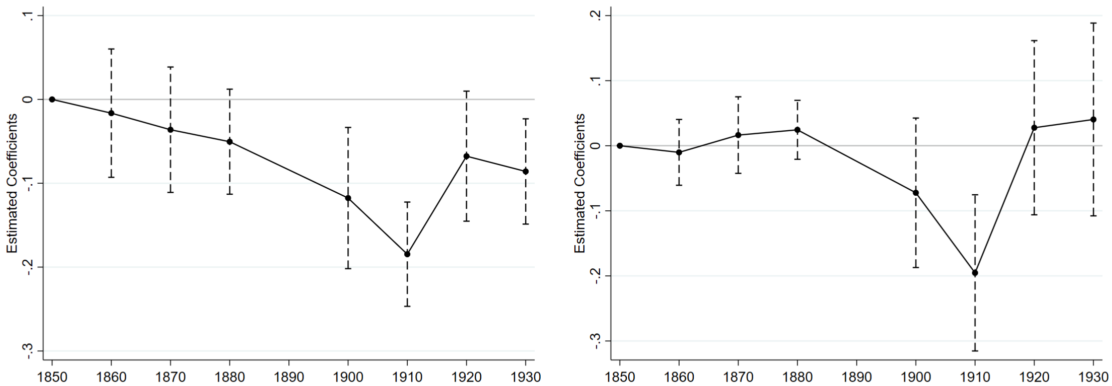


Figure A2: SLAVERY AND THE RETURN TO LITERACY IN MANUFACTURING: ROBUSTNESS

Notes: The additional county controls include the share of farmland, agricultural yield per acre, share of the manufacturing population, average manufacturing wage, and manufacturing value added per worker, which are measured for 1860. They are interacted with the literacy variable and have time-varying coefficients.

The heterogeneity across industries is also robust. Figure reffig:f$_r$*eturnlit*$_s$*kill*$_r$*obustshowsthecoefffici*
andhigh–skillindustrieswiththeadditionalcontrols, whicharecomparabletothebaselinedifferencesinFig
skillindustries, thereturntoliteracyinhigh–skillindustriesdoesnotshowdifferentialtrendsacrossthesam



(a) Low-skill industries

(b) High-skill industries

Figure A3: SLAVERY AND RETURN TO LITERACY IN MANUFACTURING IN LOW- AND HIGH-SKILL INDUSTRIES: ROBUSTNESS

Notes: The additional controls include the share of manufacturing population, manufacturing productivity, average manufacturing wage, share of farmland, and farm productivity, which are measured for 1860. They are interacted with the literacy variable and have time-varying coefficients.

C Placebo Test

The exclusion restriction for our IV strategy would not be satisfied if the potential share of the slave crops had a direct impact on patent activities. For example, specialization in the production of labor-intensive crops may have deterred industrialization (e.g., Vollrath, 2011), with potential implications for the extent of innovation. Otherwise, climate-induced variation in crop mix could have affected local industrial structure through input-output linkages, which may have influenced the direction of technical change.

To alleviate these concerns, we suggest a placebo test that investigates the relationship between the potential share of the slave crops and patent activities among non-Southern counties. The estimation follows the equation below:

$$Y_{ct} = \alpha + \beta \text{ Instrument}_c \times \text{Post} + \delta_c + \delta_{st} + \epsilon_{ct} \tag{A4}$$

Instrument_c indicates the potential share of the slave crops in county c, which is estimated from Equation 5 using the sample of non-southern counties. The coefficient β measures the reduced form effect of the potential share of the slave crop on the patent variables. Our exclusion restriction is that the IV affects patent activities exclusively through the prevalence of the slave population. If this premise holds, the estimated values of β based upon the non-South sample are expected to not significantly deviate from zero.

Table A4 presents the reduced form estimation results. For comparison, Columns (1) to (3) show the results using our baseline sample. In line with the IV estimates, the reduced form estimates support the negative link between slavery and industrial innovation after the Civil War (Panel A), which became evident only during the post-Reconstruction period (Panels B and C). Moreover, the smaller coefficients from high-skill patents confirm that the effect of slavery on technical change after Reconstruction was more evident in low-skill industries.

The results of the placebo test are not comparable. In Columns (4) to (6), we show the reduced form estimates based on the sample of non-southern counties, which do not correspond to the baseline findings. As shown in Panel C, the potential share of the slave crops does not display a negative association with industrial innovation after Reconstruction. The results in Panel A confirm that this interpretation does not change when using the Civil War as the treatment period. The heterogeneity in the reduced form results between southern and non-southern counties substantiates that the effects of the potential share of the slave crops come exclusively from the prevalence of slavery, which supports the validity of the exclusion restriction of our IV strategy.

Table A4: CIVIL WAR AND INNOVATION: REDUCED FORM AND PLACEBO TEST

Dependent variable: log number of manufacturing patents per thousand workers						
	Southern counties			Non-Southern counties		
	Total	Low	High	Total	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
A. post-Civil War						
Pot. share of slave crops	-0.552	-0.841	-0.123	-0.017	0.634	0.017
× post-Civil War	(0.273)	(0.242)	(0.168)	(0.636)	(0.594)	(0.085)
	[0.263]	[0.246]	[0.171]	[1.056]	[1.290]	[0.087]
Observations	5,286	5,267	5,206	3,922	3,859	3,861
R-squared	0.622	0.595	0.405	0.816	0.698	0.343
B. Reconstruction						
Pot. share of slave crops	0.056	-0.389	0.011	-0.528	-0.163	0.042
× Reconstruction	(0.323)	(0.248)	(0.191)	(0.699)	(0.641)	(0.088)
	[0.316]	[0.222]	[0.178]	[1.127]	[1.289]	[0.071]
Observations	3,448	3,433	3,379	2,608	2,542	2,546
R-squared	0.611	0.558	0.405	0.816	0.732	0.370
C. post-Reconstruction						
Pot. share of slave crops	-1.285	-0.937	-0.305	1.015	1.446	-0.056
× post-Reconstruction	(0.312)	(0.290)	(0.262)	(0.629)	(0.910)	(0.167)
	[0.295]	[0.259]	[0.202]	[0.697]	[0.540]	[0.128]
Observations	3,605	3,596	3,560	2,617	2,615	2,617
R-squared	0.609	0.618	0.436	0.724	0.650	0.406
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
State-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Columns (1) to (3) report the reduced-from estimates based on the sample of Southern counties, and Columns (4) to (6) show the placebo results using the non-South sample. The explanatory variable is the potential share of the slave-crops in 1859, which is used as an instrument in Section 3. Standard errors in parentheses are clustered at the county level, and Conley standard errors with a cutoff of 100km are shown in brackets.

D Pre-Trend

A key identification assumption is that there were no differential trends in patent in relation to the local prevalence of slavery. To validate the parallel pre-trend assumption further, this section estimates the time-varying relationship between the slavery and patent variables in the antebellum period.

$$Y_{ct} = \alpha + \beta \text{ Slave}_c \times After + \delta_c + \delta_{st} + \epsilon_{ct} \quad \text{for} \quad 1850 \leq t \leq 1860 \tag{A5}$$

The estimation follows Equation A5. The sample period is restricted to 1850 and 1860, where $After$ is a dummy variable that equals 1 for year 1860. Thus, the coefficient β measures whether patent activities had differential trends in relation to slavery before the Civil War. Table A5 reports the estimation results. None of these coefficients are statistically significant with small magnitudes, which supports the parallel pre-trend assumption.

Table A5: PRE-TRENDS IN SLAVERY AND MANUFACTURING PATENTS

Dependent variable: log number of manufacturing patents per thousand workers			
	Total	Low-skill	High-skill
	(1)	(2)	(3)
Slave proportion	0.002	0.039	-0.001
× year= 1860	(0.003)	(0.031)	(0.013)
	[0.002]	[0.019]	[0.008]
Observations	1,842	1,538	1,498
R-squared	0.679	0.649	0.549
County fixed effects	Yes	Yes	Yes
State-year fixed effects	Yes	Yes	Yes

Notes: Using the sample period of 1850 and 1860, this table reports the estimated pre-trends in the relationship between slavery and industrial innovation before the Civil War. Standard errors in parentheses are clustered at the county level, and Conley standard errors with a cutoff of 100km are shown in brackets.

E Citation-Weighted Patents

This study uses the number of patents to proxy the extent of innovation. The effectiveness of patented technologies may be of a concern with this approach. If patenting activities were not tightly linked to variation in production technologies, it might threaten the validity of our interpretation based on unskill-biased technical change.

Citation information could help address this issue. Given that a successful invention is more likely to be cited after it is patented, weighting the number of patents by the number of citations would move us closer to actual changes in technological environment. In this context, this section revisits the relationship between slavery and industrial innovation using the citation-weighted number of patents. Data on forward citations of patents are obtained from the PATSTAT database (European Patent Office, 2017), which we link to our sample of patents based on their publication numbers.

Table A6: SLAVERY AND CITATION-WEIGHTED PATENTS

Dependent variable: log citation-weighted number of patens per thousand workers						
	Total manufacturing		Low-skill industries		High-skill industries	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
A. post-Civil War						
Slave proportion	0.211	-1.160	0.182	-0.930	-0.001	-0.093
× post-Civil War	(0.252)	(0.541)	(0.202)	(0.432)	(0.033)	(0.075)
	[0.218]	[0.501]	[0.175]	[0.422]	[0.033]	[0.066]
Observations	5,286	5,286	5,480	5,480	5,468	5,468
R-squared	0.568		0.496		0.262	
Kleibergen–Paap F-statistic		247.92		268.02		260.75
B. Reconstruction						
Slave proportion	0.554	0.262	0.469	0.067	0.034	-0.020
× Reconstruction	(0.281)	(0.581)	(0.220)	(0.419)	(0.034)	(0.085)
	[0.222]	[0.494]	[0.176]	[0.359]	[0.027]	[0.070]
Observations	3,448	3,448	3,641	3,641	3,632	3,632
R-squared	0.536		0.455		0.301	
Kleibergen–Paap F-statistic		252.32		267.71		259.33
C. post-Reconstruction						
Slave proportion	-0.887	-2.749	-0.571	-2.083	-0.077	-0.148
× post-Reconstruction	(0.310)	(0.619)	(0.278)	(0.577)	(0.057)	(0.129)
	[0.238]	[0.504]	[0.199]	[0.554]	[0.055]	[0.105]
Observations	3,605	3,605	3,667	3,667	3,665	3,665
R-squared	0.589		0.551		0.332	
Kleibergen–Paap F-statistic		275.18		266.03		260.98
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
State-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The outcome variable is the log number of patents per thousand workers weighted by the number of citations. Standard errors in parentheses are clustered at the county level, and Conley standard errors with a cutoff of 100km are shown in brackets.

Table A6 shows the estimates using the number of patents weighted by forward citations. The results are consistent with the baseline findings. As shown in Columns (1) and (2) in Panel C, manufacturing patents declined significantly after Reconstruction, and the corresponding estimates in Panels A and B confirm the role of the end of Reconstruction as a critical juncture. Columns (3) and (4) show that the estimation based on low-skill patents exhibits a similar pattern. In contrast, the results using high-skill patents in Columns (5) and (6) are not comparable. The coefficients are small in all specifications with low statistical significance, which suggests that the relationship between slavery and high-skill patents did not experience any significant break during the sample period. The differential patterns between low- and high-skill patents support the more pronounced relationship between slavery and unskill-biased technical change in low-skill industries.

F Manufacturing Productivity

Despite evidence of the negative link between slavery and innovation, its influence on industrial productivity may still be questionable. For example, if the impact of slavery on unskill-biased technical change was complementary to the existing local industrial structure, the decline in innovation may not necessarily imply a decline in industrial productivity. For a comprehensive understanding of the legacy of slavery on industrial development, we need to clarify the productivity implications of the reduced innovation.

In this regard, Table A7 estimates the time-varying effects of slavery on manufacturing value added per worker and average manufacturing wage, which proxy for the average and marginal labor productivity in the industrial sector.[24] The results are comparable to the findings from the patent data. Columns (1) and (2) in Panel A suggest a negative link between slavery and manufacturing value added in the postbellum period, but the corresponding results in Panels B and C substantiate that this relationship became evident only after Reconstruction. Evidence from manufacturing wages in Columns (3) and (4) exhibits a consistent pattern. Although the post-Civil War effect was not significant as shown in Panel A, the estimates in Panel C substantiate the post-Reconstruction decline in manufacturing wage in relation to the historical prevalence of slavery.

[24]The total manufacturing value added and wages are divided by the number of manufacturing workers. Data is from Haines et al. (2010).

Table A7: SLAVERY AND MANUFACTURING PRODUCTIVITY

Dependent variable:	log(value added per worker)		log(wages per worker)	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
A. post-Civil War				
Slave proportion	-0.264	-0.649	-0.023	-0.038
× post-Civil War	(0.093)	(0.186)	(0.081)	(0.151)
	[0.095]	[0.208]	[0.097]	[0.171]
Observations	4,417	4,417	4,418	4,418
R-squared	0.555		0.625	
Kleibergen–Paap F-statistic		248.38		248.36
B. Reconstruction				
Slave proportion	-0.114	-0.394	0.236	0.363
× Reconstruction	(0.103)	(0.217)	(0.109)	(0.217)
	[0.097]	[0.225]	[0.123]	[0.221]
Observations	2,591	2,591	2,592	2,592
R-squared	0.571		0.613	
Kleibergen–Paap F-statistic		246.80		246.79
C. post-Reconstruction				
Slave proportion	-0.217	-0.418	-0.446	-0.735
× post-Reconstruction	(0.085)	(0.174)	(0.095)	(0.192)
	[0.086]	[0.146]	[0.102]	[0.187]
Observations	3,593	3,593	3,593	3,593
R-squared	0.612		0.662	
Kleibergen–Paap F-statistic		279.73		279.73
County fixed effects	Yes	Yes	Yes	Yes
State-year fixed effects	Yes	Yes	Yes	Yes

Notes: The outcome variables are the log of manufacturing value added (value manufacturing output - value raw materials) per thousand workers, and the log of total manufacturing wages per thousand workers. Standard errors in parentheses are clustered at the county level, and Conley standard errors with a cutoff of 100km are shown in brackets.

G Tables for the Return to Literacy in Manufacturing

Table A8: SLAVERY AND THE RETURN TO LITERACY IN MANUFACTURING

	Total (1)	Low-skill industries (2)	High-skill industries (3)
Slave proportion × Literacy	0.005	0.012	-0.000
× Year 1860	(0.038)	(0.037)	(0.028)
Slave proportion × Literacy	-0.031	-0.044	0.026
× Year 1870	(0.031)	(0.034)	(0.033)
Slave proportion × Literacy	-0.006	-0.037	0.052
× Year 1880	(0.027)	(0.032)	(0.021)
Slave proportion × Literacy	-0.067	-0.108	-0.054
× Year 1900	(0.047)	(0.043)	(0.078)
Slave proportion × Literacy	-0.237	-0.170	-0.247
× Year 1910	(0.064)	(0.054)	(0.123)
Slave proportion × Literacy	-0.153	-0.087	-0.059
× Year 1920	(0.044)	(0.041)	(0.065)
Slave proportion × Literacy	-0.116	-0.058	-0.024
× Year 1930	(0.039)	(0.027)	(0.098)
Observations	1,897,703	1,207,620	689,778
R-squared	0.421	0.409	0.386
County-year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes

Notes: The sample consists of white manufacturing workers aged 18-80. The outcome variable is the status of having skilled occupations. Individual controls include age, age squared, nativity, gender, urban residence, and the status of household head. Standard errors in parentheses are clustered at the county level.

Table A9: SLAVERY AND THE RETURN TO LITERACY IN MANUFACTURING: ROBUSTNESS

	Total	Low-skill industries	High-skill industries
	(1)	(2)	(3)
Slave proportion × Literacy	-0.016	-0.016	-0.010
× Year 1860	(0.037)	(0.039)	(0.026)
Slave proportion × Literacy	-0.029	-0.036	0.016
× Year 1870	(0.032)	(0.038)	(0.030)
Slave proportion × Literacy	-0.023	-0.050	0.024
× Year 1880	(0.028)	(0.032)	(0.023)
Slave proportion × Literacy	-0.071	-0.118	-0.072
× Year 1900	(0.041)	(0.043)	(0.059)
Slave proportion × Literacy	-0.253	-0.185	-0.195
× Year 1910	(0.034)	(0.032)	(0.061)
Slave proportion × Literacy	-0.119	-0.068	0.028
× Year 1920	(0.040)	(0.040)	(0.068)
Slave proportion × Literacy	-0.131	-0.086	0.040
× Year 1930	(0.036)	(0.032)	(0.075)
Observations	1,797,366	1,144,747	652,427
R-squared	0.415	0.401	0.384
County-year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes

Notes: The sample consists of white manufacturing workers aged 18-80. The outcome variable is a dummy variable for skilled occupations. Individual controls include age, age squared, nativity, gender, urban residence, and the status of household head. Standard errors in parentheses are clustered at the county level.