Technological Progress in Slack Labor Markets

Vincent DELABASTITA [1]
Maarten GOOS[2,3,4]

[1]Radboud University
[2]Utrecht University
[3]Instituut Gak
[4]Tilburg University

June 2025

This paper shows that technological progress changes relative wages through its impact on labor relations. The paper first presents a simple monopsony model in which firms have wage-setting power because workers are in excess supply, and technological progress erodes firms' monopsony power by increasing labor market tightness. Although technological progress is factor neutral, the model predicts that lower-tail wage inequality decreases. These predictions are then corroborated using unique census data from Belgium's Second Industrial Revolution between 1846 and 1896. Instrumental Variables estimates show that lower-tail wage inequality fell more in industries and regions where the adoption of steam engines was higher.

Keywords: Monopsony, excess labor supply, wage growth, Industrial Revolution
JEL: J21, J31, N33

Helpful comments by Erik Buyst, Sebastiaan Maes, and Judy Stephenson are gratefully acknowledged. We also would like to thank numerous seminar participants for suggestions and discussions. Vincent Delabastita benefited from a PhD Fellowship (Aspirant) of the Research Foundation - Flanders (FWO), grant number 11F8619N. Finally, Michel Berghs, André Davids and the team of *Project Belgische historische tellingen* (KU Leuven) provided invaluable data assistance.

1. Introduction

The impact of technological progress on average living standards and income inequality is one of the most studied questions among economists and economic historians. Popular belief is that average living standards started to increase in western Europe with the commercialization of steam power and the arrival of the First Industrial Revolution in about 1750. However, most economic historians would agree that in the early decades of the First Industrial Revolution, the adoption of steam power in coal mining and textile production did not result in higher real wages in these sectors.[1] An explanation for the slow growth of real wages could be that labor demand decreased with the adoption of steam pumps to drain water from coal mines and steam-powered spindles and looms to automate the production of textiles.[2]

In this paper, we add to this literature by focusing on the first decades of average real wage growth during the Second Industrial Revolution, from about 1840 to 1900, when steam engines became broadly adopted but trade unions or other channels of workers' voice were not yet recognized and often forbidden. In particular, this paper argues that the widespread adoption of steam power dissipated an economy-wide problem of excess labor supply, which caused a change in the nature of labor relations from a monopsonistic toward a more competitive labor market. To formalize the intuition, we present a simple monopsony model that predicts average real wage growth when the balance of power between firms and workers shifts in favor of workers due to technological progress that complements workers. Although the model assumes that technological progress complements all workers equally, the model also predicts a decrease in lower-tail wage inequality if some firms adopt new technologies more intensively than others. The intuition for this is that low-wage workers experience stronger relative wage growth and disproportionately relocate from the lowest-wage firms that are less technology intensive toward higher-wage firms that are more technology intensive.

To test our model's predictions, this paper then uses data from Belgium's industrial

[1] The timing and extent of real wage increases following the Industrial Revolution were subject to one of the fiercest debates in the field of economic history (typically dubbed as the 'living standards debate'), with optimistic (Lindert and Williamson 1983; Clark 2005) and pessimistic (Feinstein 1998; Allen 2009) views. In general, the literature appears to agree that real wage growth was relatively modest during the early stages of industrialization (Gallardo-Albarrán and De Jong 2021; Humphries and Weisdorf 2019; Federico, Nuvolari, and Vasta 2023).

[2] For such a perspective, see Acemoglu and Restrepo (2019). In another interpretation, Crafts and Mills (2022) points to the role of demographic expansion as a depressing force on real wage growth.

censuses in 1846 and 1896. The choice for these data is motivated by Belgium's historical context, as well as unique data access. First, Belgium's historical context between 1846 and 1896 was that due to its high population density, manufacturing firms could easily tap into low-cost labor. Moreover, labor markets remained largely unregulated until the early twentieth century, as lawmakers held true to the free-market principles on which Belgium was founded in 1830. As a result of an excess supply of workers and unregulated labor markets, the balance of power between firms and workers was initially tilted in favor of firms. However, in the following decades the Belgian economy experienced rapid technological progress, being the first country on the European continent to industrialize through the widespread adoption of steam engines in manufacturing, which transformed labor markets and labor relations.

Second, the uniqueness of Belgium's 1846 and 1896 Industrial Censuses makes an analysis particularly interesting for two reasons. First, based on wage information on every manufacturing worker in 1846 and 1896, we observe (relative) wages in each of 19 manufacturing sectors in 41 geographical districts. This detailed wage information allows us to estimate changes in wage dispersion without having to rely on estimating skill premia, which usually requires hard-to-verify assumptions in historical data.[3] Second, in each census we observe the use of steam-based machinery expressed in horsepower, which gives us a unique and comparable measure of technology adoption across detailed sector-district cells.

In our analyses, the driver of average wage growth and the compression of lower-tail wage inequality is the widespread adoption of steam power which increased labor demand, thereby reducing excess labor supply. This shifted the balance of power away from firms and towards workers, resulting in less monopsonistic and more competitive labor markets. That excess labor supply was an important source of monopsony power in the early decades of industrialization also follows from the views of labor economists at the time. The dominant view was that the most important source of unequal bargaining power for workers was that most urban labor markets experienced a chronic excess supply of unskilled labor, due to large-scale migration from farm to city and long periods of recession and depression. For example, Sidney and Beatrice Webb wrote in 1897:

[3] For instance, Clark (2007, 225) points to the relative stability of the skill premium in the English building sector to argue that the Industrial Revolution was not skill-biased. However, Mokyr and Voth (2010) questions the restricted focus of Clark on the building sector. Another example questioning the use of skill premia in a British context is Feinstein (1988), whose criticism of Williamson (1985) illustrates the difficulties in constructing reliable and representative measures of relative wages.

> *"When the unemployed are crowding round the factory gates every morning, it is plain to each man that, unless he can induce the foreman to select him rather than another, his chance of subsistence for weeks to come may be irretrievably lost. Under these circumstances, bargaining, in the case of the isolated individual workmen, becomes absolutely impossible. The foreman has only to pick his man, and tell him the terms. Once inside the gates, the lucky workman knows that if he grumbles at any of the surroundings, however, intolerable; if he demurs to any speeding-up, lengthening of the hours, or deduction; or if he hesitates to obey any order, however unreasonable, he condemns himself once more to the semi-starvation and misery of unemployment. For the alternative to the foreman is merely to pick another man from the eager crowd, whilst the difference to the employer becomes incalculably infinitesimal."* (1897, 660)

This idea was further developed by early institutional labor economists in the first half of the twentieth century.[4] Although they recognized that wage adjustments play an important role in allocating labor and maintaining a balance between demand and supply, they also believed that allowing the general level of wages and labor conditions to fall in response to widespread unemployment is most often ineffective and even counterproductive (Commons 1921; Slichter 1931). The reasoning, anticipating Keynes, is that wage cuts in slack labor markets will fail to reduce unemployment because of firms' increased wage-setting power. This paper returns to this hypothesis.

More recent studies of technological progress assume mainly that labor markets are perfectly competitive.[5] In many growth models, including the textbook Solow model, average real wages grow along a balanced growth path following technological progress (Acemoglu and Restrepo 2018; Caselli and Manning 2019). This happens because technological progress not only increases output per worker, but also makes employment more valuable to employers, which in a competitive labor market will increase average real wages. Most recently, however, a literature has emerged in which technological progress does not need to result in real wage growth for each worker. One reason is

[4]Prominent examples are John Commons, Paul Douglas, Richard Ely, Harry Millis, and Sumner Slichter. Their ideas were in turn adopted by a younger generation of neoinstitutional labor economists, such as John Dunlop, William Kerr, Richard Lester, and Lloyd Reynolds, and under their influence dominated research in labor economics up to the 1970s. From 1980 onward, this tradition has been displaced by a more neoclassical approach to labor markets, although it remains the intellectual core of the field of industrial relations.

[5]One exception is Azar et al. (2023) who find that automation technologies lead to larger wage losses for workers in monopsonistic labor markets.

that the nature of technological progress can be such that it automates the tasks done by some workers, thus decreasing their marginal product of labor (Autor, Levy, and Murnane 2003). Another reason is that some workers cannot reap the benefits of an increase in average labor productivity because labor markets are imperfectly competitive and the balance of power is tilted in favor of firms (Acemoglu and Restrepo 2022). We add to this more recent literature by arguing that there is a close relationship between technological progress, changes in the balance of power between firms and workers, and changes in average and relative wages.

This paper also builds on several recent studies that examine imperfectly competitive labor markets. First, Dustmann et al. (2022) builds on the static monopsony model of Card et al. (2018) in which workers have heterogeneous preferences over firms to argue why higher minimum wages reduce lower-tail wage inequality and cause a reallocation of employment from low-wage to high-wage firms. Second, Autor, Dube, and McGrew (2023) argues that this framework can also be used to explain the recent decrease in lower-tail wage inequality in the US. They argue that, similar to an increase in the minimum wage, post-pandemic labor shortages effectively increased the elasticity of firm-level supply. To do so, they refer to static and dynamic monopsony models in which firms' wage setting power decreases when workers' job offer arrival rates increase.[6] Their paper is closest to ours. One important difference is that monopsony power in our model originates from an employer's discretion to pick workers if there is an excess supply of labor. We model this by introducing the difference between a job application and a job offer. If there are many job applicants because there is an excess supply of workers, relatively few applicants will receive a job offer. Therefore, workers who receive a job offer "feel lucky" and firms exploit this by offering lower wages. Consequently, if labor market tightness increases due to technological progress, firms' monopsony power decreases, the average real wage increases, and lower-tail wage inequality decreases.

Our paper also relates to recent studies that examine the Industrial Revolution. Voth, Caprettini, and Trew (2024) argue that the British Industrial Revolution was an example of directed technological change. They use the French Revolutionary and Napoleonic

[6] See Manning (2021) for a review of static and dynamic monopsony models. He refers to static monopsony models as "new classical monopsony" and to dynamic monopsony models as "modern monopsony". He also conjectures about the promise of combining both sources of monopsony power into a single framework, which he coins "thoroughly modern monopsony". Our simple model below aims to take a small step in this direction.

Wars (1793-1815), which required a rapid expansion of Britain's armed forces, leading to significant shortages of labor supply in areas where naval recruitment was higher. Using warships' ease of access to coastal locations as an instrument, they show that exogenous shocks to labor scarcity led to technology adoption. Our paper supports this view by arguing that manufacturing firms could easily tap into cheap labor because firms had wage-setting power, incentivizing firms to develop steam technologies that complemented workers.[7] In line with this, Rubens (2024) finds that monopsony power encouraged coal mines to adopt mechanical coal cutters in 19th-century Illinois.

Like ours, some studies have focused on the importance of labor market imperfections during industrialization. Ashraf et al. (2024) argue that the decline of coercive labor institutions over the course of industrialization was partly driven by the complementarity between physical capital and effective labor in manufacturing. Given the difficulty of extracting labor effort in industrial tasks through monitoring and punishment, capital-owning elites chose to emancipate their serfs to induce their effort and thus boost the return to physical capital. They examine this hypothesis in the context of Prussian watermill owners choosing to emancipate their workers between 1821 and 1848. Our paper does not assume that technology induces firms to pay efficiency wages. Instead, we argue that labor relations changed because competition between firms for workers increased due to technological progress. However, Delabastita and Rubens (2025) show that this does not mean that labor markets remained imperfectly competitive in some cases: they show that employer collusion between 227 Belgian coal firms resulted in substantial wage markdowns between 1845 and 1913.

Focusing on wealth inequality, Reichardt (2025) shows that the adoption of steam power in the US and the Netherlands increased wealth inequality, while the adoption of electric power had the opposite effect. To explain these findings, he assumes a model of monopolistic competition in which firms differ in their productivity, and steam but not electric power has high sunk costs. Consequently, relatively fewer highly productive entrepreneurs will dominate product markets after having invested in steam relative to electric power, resulting in higher wealth inequality when sunk costs are higher. Juhasz, Squicciarini, and Voigtlaender (2024) also examine the importance of firm heterogeneity for the adoption of mechanized cotton spinning during the First Industrial Revolution in France. The find that a trial-and-error process in reorganizing production

[7]Similarly, Mokyr (1976) argues that the presence in Belgium of a dense network of a part-time peasant industry, with a consequent low level of wages and a high supply elasticity of labor, drove Belgium's industrial development.

led to initially low and widely dispersed productivity between firms operating the new technology, but high productivity growth as new entrants adopted improved methods of organizing production in the long term. Fiszbein et al. (2024) also find for the US that electrification between 1890 and 1940 was accompanied by capital deepening and organizational changes that increased productivity, especially for larger firms. Our paper complements these studies. However, it does not focus on entrepreneurial income and wealth inequality. Our paper also does not directly examine the importance of firm heterogeneity and productivity growth.

The paper is structured as follows. In Section 2, we present a simple monopsony model that predicts average real wage growth and a decrease in lower-tail wage inequality if technological progress also decreases firms' wage-setting power. Section 3 then introduces the historical context. Next, Section 4 discusses our main data based on the Belgian Industrial Censuses of 1846 and 1896, which contains detailed sectoral information on wages, employment, and the use of steam engines. Using these data, Section 6 provides empirical evidence that the adoption of steam engines resulted in a decrease in lower-tail wage inequality. Section 7 considers alternative explanations. Finally, Section 8 concludes.

2. A model

2.1. Graphical summary of the model

This subsection provides a graphical summary of our more formal model. Before 1850, workers' chances of a successful job application were low because of a high population density together with limited growth in manufacturing labor demand. This lack of job opportunities also meant that workers who received job offers "felt lucky" and that the balance of power between firms and workers was in favor of firms. This gave companies the ability to set wages, which is captured by the solid upward-sloping labor supply curves (LS) in panels A and B of Figure 1. The marginal cost of labor (MC_L) curves draw the corresponding marginal labor costs if the firm cannot discriminate between workers. In this sluggish labor market, equilibrium employment is given by the intersection of the MCL curve and the downward-sloping marginal product of labor (MP_L) curve.

The broad adoption of steam power across manufacturing sectors after 1850 increased manufacturing labor demand and thereby workers' chances of a successful job application. Consequently, workers became less desperate to accept a job offer, which shifted the balance of power between firms and workers in favor of workers. The decrease in the firm's wage setting power is captured by an increase in the elasticity of the firm's labor supply curves in panels A and B of Figure 1. The dashed *LS* curves in both panels indicate that wages, and therefore also the average real wage, grow because of the decrease in firms' monopsony power.

Figure 1 further illustrates what happens to relative wages and employment when labor markets become more competitive and firms differ in productivity. The vertical axes show that a more elastic labor supply results in a larger wage increase in low-productivity firms (panel A) than in high-productivity firms (panel B). An interpretation of this result is that increased competition between firms for workers requires low-wage firms to increase their wages by more than high-wage firms. Consequently, technology-induced increases in competition between firms for workers cause a decrease in lower-tail wage inequality. The horizontal axes of Figure 1 show that lower-tail wage inequality further decreases due to the reallocation of workers from low-productivity to high-productivity employers, because the only way in which low-productivity firms can increase their relative wages is by employing relatively fewer workers.

2.2. The balance of power between firms and workers

Following Card et al. (2018), assume that each firm j posts a single wage w_j to attract workers. Among all the posted wages, each worker then chooses to apply to a single firm. Assume that utility of worker i from working at firm j is given by:

$$u_{ij} = \epsilon[\ln(w_j) + \ln(\theta(w_j))] + \eta_{ij} \text{ with } \epsilon \geqslant 0 \tag{1}$$

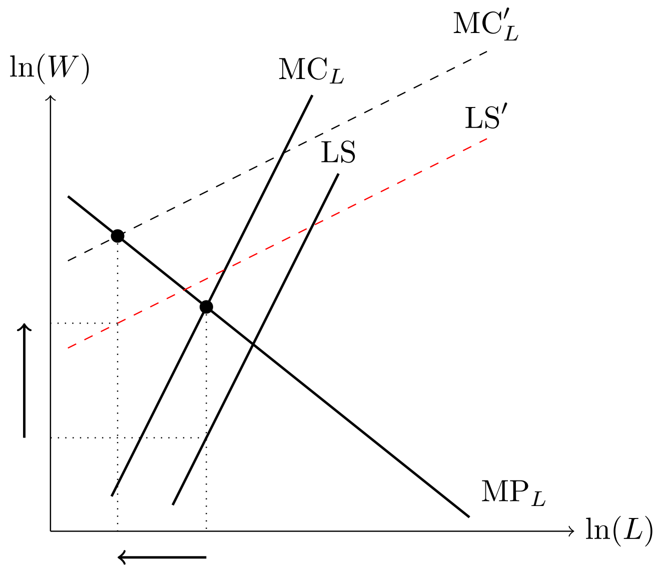
with $w_j\theta(w_j)$ the expected wage at firm j, which is the product of two terms. First, w_j is the wage earned if worker i is hired by firm j. Second, $0 \leqslant \theta(w_j) \leqslant 1$ is the probability of getting a job offer from firm j given that worker i applied to that firm. The term η_{ij} is an idiosyncratic preference term for the firm's non-wage characteristics. Examples are match-specific factors such as travel time or interactions with coworkers and supervisors. Finally, ϵ captures workers' preferences for expected wage income relative to the firm's non-wage characteristics.

We further assume that the probability of a successful application, $0 \leqslant \theta(w_j) \leqslant 1$, is decreasing in w_j as follows:

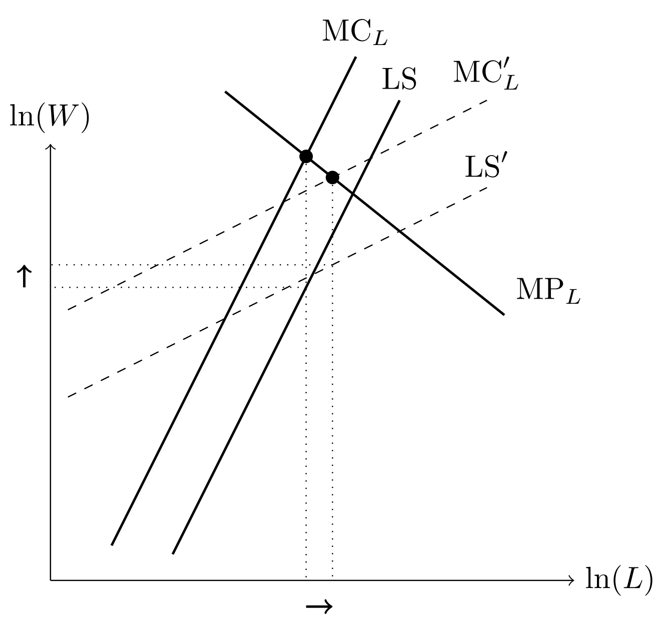
$$\ln(\theta(w_j)) = -\epsilon_{\theta w} \ln(w_j) \text{ with } \epsilon_{\theta w} \geqslant 0 \tag{2}$$

FIGURE 1. Technological progress in slack labor markets

A. Low-productivity firm



B. High-productivity firm



where the minus sign follows from the assumption that an increase in w_j reduces $\theta(w_j)$. The intuition for this is that a higher wage offer will attract more applications, which reduces each applicant's probability of receiving a job offer. $\epsilon_{\theta w}$ is the elasticity of a successful application with respect to the wage paid by firm j.

Importantly, we assume that $\epsilon_{\theta w}$ is greater in slack labor markets. This captures the fact that workers value the probability of receiving a job offer more when there is an excess supply of workers. In particular, workers dislike lower wages relatively less when labor markets are sluggish because they value the job offer relatively more. In this way, a greater $\epsilon_{\theta w}$ formalizes the intuition of the previous subsection that workers who receive a job offer "feel lucky" when there is an overall excess supply of labor. We will show below that, therefore, firms will offer lower wages because the labor supply to the firm is more inelastic in slack labor markets.

When aggregate labor demand increases such that excess labor supply decreases, $\epsilon_{\theta w}$ decreases over time and the balance of power between firms and workers shifts towards workers. We assume that this is what happened with the widespread adoption of steam-based manufacturing during Belgium's Industrial Revolution. In the extreme case of $\epsilon_{\theta w} = 0$, we have that $\theta(w_j) = 1$ such that every job application is successful.[8]

2.3. The elasticity of firm-level labor supply

This subsection formally shows that a decrease in $\epsilon_{\theta w}$ increases the elasticity of firm-level labor supply.

2.3.1. Firm-level labor supply

If $\{\eta_{ij}\}$ are independent draws from a type-I Extreme Value distribution, the number of applications to firm j is given by:

$$a_j = \frac{\exp\left(\epsilon[\ln(w_j) + \ln(\theta(w_j))]\right)}{\sum_{k=1}^{J} \exp\left(\epsilon[\ln(w_k) + \ln(\theta(w_k)]\right)} \tilde{L} \tag{3}$$

with $\tilde{L}$ the total number of job applicants.

To simplify the analyses and abstract from strategic interactions in wage setting,

[8]Note that if $\epsilon_{\theta w} \to \infty$, we have that $\theta(w_j) \to 0$. In this case, no application is successful, which cannot be true. In the following, we exclude this possibility by assuming that $0 \leqslant \epsilon_{\theta w} \leqslant \epsilon/(1+\epsilon)$.

assume that the number of firms J is large such that we can write:

$$\ln(a_j) = \epsilon[\ln(w_j) + \ln(\theta(w_j))] + \ln(\lambda\tilde{L}) \tag{4}$$

where λ is a constant common across all firms. Using Equation (4) and the fact that firm-level employment can be defined as $l_j \equiv a_j \theta(w_j)$, labor supply to the firm is given by:

$$\ln(l_j) = [\epsilon(1 - \epsilon_{\theta w}) - \epsilon_{\theta w}] \ln(w_j) + \ln(\lambda\tilde{L}) \tag{5}$$

2.3.2. The elasticity of firm-level labor supply

Using Equations (2) and (4), the elasticity of firm-level applications w.r.t. wages is given by:

$$\epsilon_{aw} \equiv \frac{d\ln(a_j)}{d\ln(w_j)} = \epsilon(1 - \epsilon_{\theta w}) \tag{6}$$

which shows that ϵ_{aw} is decreasing in $\epsilon_{\theta w}$.[9]

From Equation (5), the elasticity of firm-level labor supply is given by:

$$\epsilon_{lw} \equiv \frac{d\ln(l_j)}{d\ln(w_j)} = \epsilon(1 - \epsilon_{\theta w}) - \epsilon_{\theta w} = \epsilon - (1 + \epsilon)\epsilon_{\theta w} \tag{7}$$

which shows that ϵ_{lw} is decreasing in $\epsilon_{\theta w}$.[10] To ensure that $\epsilon_{lw} \geqslant 0$ or that firm-level labor supply is upward sloping, we assume that $0 \leqslant \epsilon_{\theta w} \leqslant \epsilon/(1+\epsilon)$. Note that a decrease in $\epsilon_{\theta w}$ increases ϵ_{lw}. That is, firm-level labor supply becomes more elastic if the balance of power shifts towards workers, as was graphically illustrated in Figure 1. If $\epsilon_{\theta w} = 0$ and $\epsilon \to \infty$, we get $\epsilon_{lw} \to \infty$. In this limiting case, the law of one wage holds because labor markets are perfectly competitive.

[9] Estimates of ϵ_{aw} for current labor markets are around 0.5. See Manning (2021) for a discussion.

[10] Estimates of ϵ_{lw} for current labor markets are between 0 and 6. See Langella and Manning (2021).

2.4. Wage setting by firms

Assume that firms have the following production function:

$$q_j = \psi_j \ln(l_j) \tag{8}$$

where ψ_j is firm-specific productivity. Firms maximize profits by posting a wage that minimizes labor costs given Equation (5):[11]

$$\max_{w_j} \left[\psi_j \ln(l_j) - w_j l_j\right] \quad \text{s.t.} \quad l_j = l_j(w_j) \tag{9}$$

The first-order conditions are given by:

$$\psi_j \frac{1}{l_j} \frac{dl_j(w_j)}{dw_j} = l_j + w_j \frac{dl_j(w_j)}{dw_j}$$

Using the definition of ϵ_{lw}, this can be written as:

$$w_j = \left(\frac{\epsilon_{lw}}{1+\epsilon_{lw}}\right) \frac{\psi_j}{l_j} \tag{10}$$

which shows that wages are a markdown of marginal labor productivity. Moreover, note that Equation (7) implies that:

$$\frac{\epsilon_{lw}}{1+\epsilon_{lw}} = \frac{\epsilon - (1+\epsilon)\epsilon_{\theta w}}{(1+\epsilon)(1-\epsilon_{\theta w})}$$

Substituting this into Equation (10) and taking logs gives:

$$\ln(w_j) = \ln\left(\psi_j \frac{\epsilon - (1+\epsilon)\epsilon_{\theta w}}{(1+\epsilon)(1-\epsilon_{\theta w})}\right) - \ln(l_j) \tag{11}$$

Combining Equations (2), (4), (5) and (11), equilibrium expressions for wages and

[11] We assume employers do not observe worker preferences for firm-specific non-wage amenities. This implies that employers cannot discriminate between workers: if a firm wants to hire more workers, it needs to offer higher wages to all workers. Also note that product markets are assumed to be perfectly competitive.

employment can be derived.[12] Firm-specific equilibrium wages are given by:

$$\ln(w_j) = \underbrace{\frac{1}{(1+\epsilon)(1-\epsilon_{\theta w})} \ln\left(\psi_j \frac{\epsilon - (1+\epsilon)\epsilon_{\theta w}}{(1+\epsilon)(1-\epsilon_{\theta w})}\right)}_{\equiv A} - \frac{1}{(1+\epsilon)(1-\epsilon_{\theta w})} \ln(\lambda\tilde{L}) \tag{12}$$

where the right-hand side only depends on the model's parameters. Firm-level employment in equilibrium is given by:

$$\ln(l_j) = \underbrace{\frac{\epsilon - (1+\epsilon)\epsilon_{\theta w}}{(1+\epsilon)(1-\epsilon_{\theta w})} \ln\left(\psi_j \frac{\epsilon - (1+\epsilon)\epsilon_{\theta w}}{(1+\epsilon)(1-\epsilon_{\theta w})}\right)}_{\equiv B} + \frac{1}{(1+\epsilon)(1-\epsilon_{\theta w})} \ln(\lambda\tilde{L}) \tag{13}$$

Note that terms A in Equation (12) and B in Equation (13) are firm-specific, showing that relatively more productive firms (i.e. firms with higher ψ_j) pay higher wages and employ more workers.

2.5. Comparative statics when the balance of power shifts towards workers

We first show that the average real wage grows when firms' wage-setting power decreases. We then show that our model also predicts that lower-tail wage inequality decreases because relative wages of low-wage workers increase and because workers relocate from low-wage to higher-wage firms.

2.5.1. Average real wage growth

The economy-wide average real wage is given by the employment-weighted average of firm-specific wages:

$$\bar{w} = \sum_j \frac{l_j}{L} w_j$$

with L the total number of jobs. Using Equation (10), this can be rewritten as:

$$\bar{w} = \frac{1}{L}\left(\frac{\epsilon_{lw}}{1+\epsilon_{lw}}\right) \sum_j \psi_j \tag{14}$$

[12] See Appendix A.1 for details.

If labor markets are perfectly competitive or $\epsilon_{lw} \to \infty$, the term in brackets in Equation (14) becomes unity. In this extreme case, technological progress directly results in average real wage growth. This result is consistent with the existence of a "productivity bandwagon" in competitive models.[13] Moreover, equation (14) shows that changes in the balance of power between firms and workers can either slow down (if ϵ_{lw} decreases because $\epsilon_{\theta w}$ increases) or speed up (if ϵ_{lw} increases because $\epsilon_{\theta w}$ decreases) this productivity bandwagon. Importantly, we argue that part of the growth in average real wages in the Industrial Revolution was driven by an increase in ϵ_{lw}.

2.5.2. Changes in relative wages and employment

Our model also predicts that a decrease in $\epsilon_{\theta w}$ results in a decrease in lower-tail wage inequality because the relative wages of low-wage workers increase and low-wage workers relocate to high-wage firms, as illustrated in Figure 1.

To see what happens to relative wages and employment when $\epsilon_{\theta w}$ decreases, we can differentiate the firm-specific terms A in Equation (12) and B in Equation (13) w.r.t. $\epsilon_{\theta w}$.[14] Deriving term A in Equation (12) w.r.t. a decrease in $\epsilon_{\theta w}$ gives:

$$-\frac{\partial A}{\partial \epsilon_{\theta w}} = \frac{1}{(1+\epsilon)(1-\epsilon_{\theta w})^2}\left[\frac{1}{\epsilon-(1+\epsilon)\epsilon_{\theta w}} - \ln\left(\psi_j \frac{\epsilon-(1+\epsilon)\epsilon_{\theta w}}{(1+\epsilon)(1-\epsilon_{\theta w})}\right)\right] \tag{15}$$

which is decreasing in ψ_j.

From Equation (13) it is straightforward to see that a decrease in $\epsilon_{\theta w}$ will also increase relative employment in firms with higher ψ_j. More formally, differentiating term B in Equation (13) w.r.t. a decrease in $\epsilon_{\theta w}$ gives:

$$-\frac{\partial B}{\partial \epsilon_{\theta w}} = \frac{1}{(1+\epsilon)(1-\epsilon_{\theta w})^2}\left[1 + \ln\left(\psi_j \frac{\epsilon-(1+\epsilon)\epsilon_{\theta w}}{(1+\epsilon)(1-\epsilon_{\theta w})}\right)\right] \tag{16}$$

which is increasing in ψ_j.

In conclusion, our model predicts average real wage growth in slack labor markets when technological progress complements workers and diminishes the wage-setting power of firms. Furthermore, it predicts that technological progress compresses lower-

[13] Acemoglu and Johnson (2023) coin the term "productivity bandwagon" to describe the increase in the average real wage due to technological progress. In line with this, Armangué-Jubert, Guner, and Ruggieri (2025) argue output per capita could increase by up to 44% in countries where GDP per capita is low if labor markets in these countries were as competitive as in more developed ones.

[14] See Appendix A.2 for details.

tail wage inequality even among identical workers. This is due to an increase in the relative wages of the lowest-wage workers and the relocation of workers from low-wage to high-wage firms. Lastly, our model suggests that both average real wage growth and the compression of lower-tail wage inequality are more pronounced in sectors and regions where the adoption of steam power was stronger.

3. Historical context

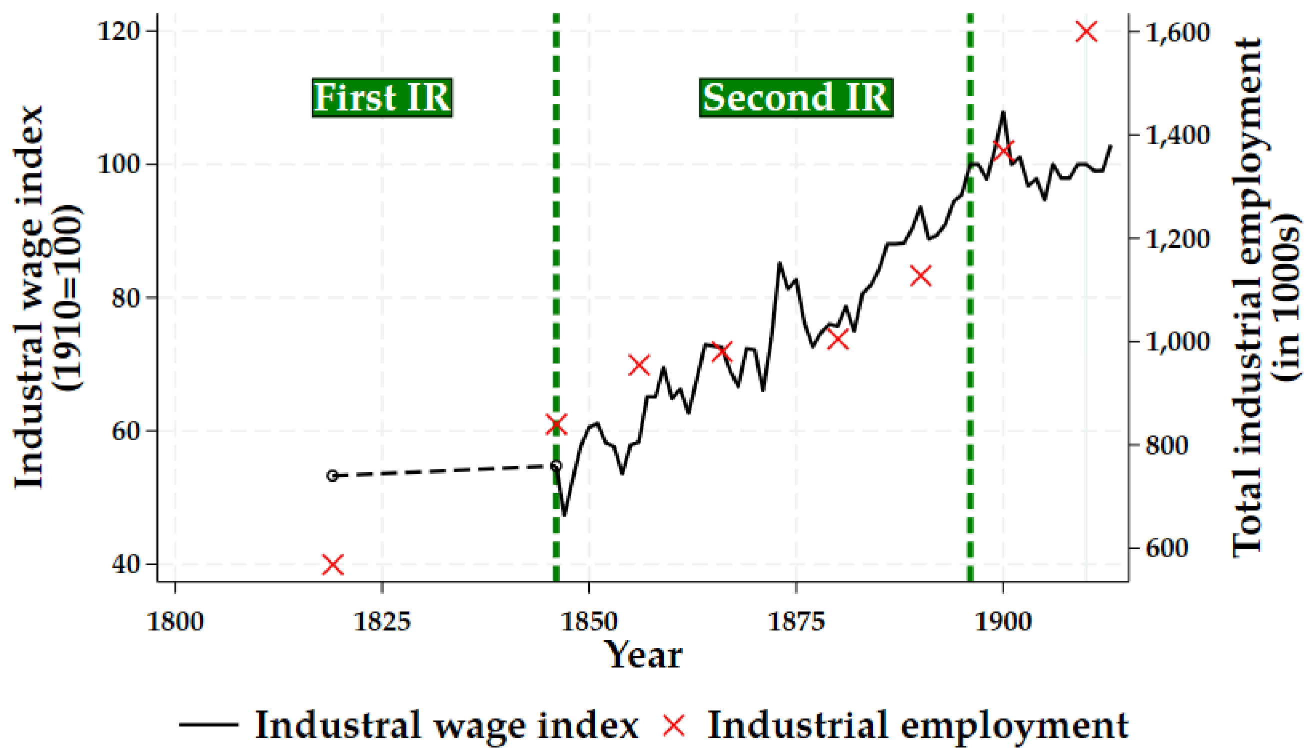
3.1. The Industrial Revolution in Belgium

Belgium was the first country on the European continent to industrialize by successfully adopting British innovations of the eighteenth and early nineteenth centuries. There are multiple plausible reasons for Belgium's success. The Southern Netherlands, which became Belgium in 1830, had a long tradition in urban and rural industries, helping the region to sustain a high population density and, therefore, a large potential workforce. Belgium was also a historical leader in commercial and financial developments (Van der Wee 1996). In addition, Belgium's Walloon area was endowed with easily accessible coal, in which local industrialists had a centuries-long tradition of commercial exploitation.[15] All these elements contributed to Belgium's industrial success.

Belgium's Industrial Revolution can be divided into its First and Second Industrial Revolutions. Beginning in Great Britain around 1760, the First Industrial Revolution had spread to Belgium by the late 18th century. This transition included going from hand-made methods to machine production methods, especially in the textile industries with inventions such as mechanized spinning and weaving using steam power. These technologies matured and became widespread across manufacturing sectors after 1850, resulting in Belgium's Second Industrial Revolution. From 1850 to 1914, the country transitioned from a primarily agricultural economy to a leading industrial nation, particularly in heavy industries such as iron, steel, and coal. This period saw the widespread adoption of steam engines, mass production techniques, and a shift in labor from rural areas to urban industrial centers.

[15] See Figure B1 in Appendix B for a detailed map of employment in coal mining in 1896.

FIGURE 2. Wage evolution and total employment growth in manufacturing during Belgium's Industrial Revolutions



Notes: The dashed lines indicate the timings of the major Belgian industrial censuses.
Sources: Employment: Buyst (Forthcoming), guesstimate for 1819 using the same methodology as in Buyst (Forthcoming). Wage indices: Segers (2003), guesstimate for 1819 based on Mokyr (1976, 180). Both series refer to adult workers.

3.2. Labor markets in the 19th century

Belgium's high population density meant that a large reserve was available to its industrial entrepreneurs, a feature that has also been identified as a driver of the country's industrial growth (Mokyr 1976). This large labor supply translated into low wages and modest, if any, wage growth during the early stages of industrialization (Mokyr 1976, 181-188). One of Belgium's foremost contemporary observers, Natalis Briavoinne, paints a vivid picture of the limited progress for the working class before 1850, referring to the "*congestion in markets, partial or total suspension of work; hence, deep misery for thousands of families*" (1839, 208).

In the late 18th century, Belgium's economy had been supported by rural linen production, particularly in the region of Flanders.[16] However, its collapse in the first decades of the 19th century, due to competition from mechanized production of cotton textiles, forced thousands of rural workers into inactivity (Jacquemyns 1929). To illustrate this, a member of Belgium's Chamber of Representatives described the case of Flemish rural workers in 1843 as (Ducpétiaux 1843, 14): *"Our unfortunate workers, who lack bread, do not ask for charity but rather for work to earn the bread needed for their subsistence and that of their families."*

The situation of workers in mechanized factories producing cotton textiles was not much better. For example, in their in-depth assessment of the strongly mechanized cotton industry in the city of Ghent, Mareska and Heyman (1845, 85) write that *"after a life of honest labor, the worker, instead of receiving a fair and adequate reward, only encounters ruin and desolation"*. Other contemporary commentaries were equally pessimistic. In 1817, a government official visited the mechanized wool factories in Verviers and commented (Mokyr 1976, 184): *"Whenever business booms and machines are introduced so that goods can be produced at a lower cost than the market price, workers continue to receive the same wages, while manufacturers gain thousands."*

After 1850, however, workers' fortunes in terms of employment opportunities and real wage growth changed dramatically. Figure 2 combines various measures from the literature of the evolution of employment and the real average wage after 1850. The black line shows that the average real wage of manufacturing workers about doubled between 1846 and 1896 (the two dashed green vertical lines corresponding to the two census years that we use in our analyses below), but also that the average real wage did

[16]Figure B2 in the Appendix B shows a detailed map of the share of rural employment in 1896.

not grow before 1846 or between 1896 and 1913. Total employment in manufacturing, indicated by the red crosses and measured on the right scale, increased by about 70 percent between 1846 and 1896. Overall, the increase in the average real wage as well as employment suggests that the demand for manufacturing workers increased in the second half of the 19th century during Belgium's Second Industrial Revolution.

However, improvements in labor market outcomes were not due to the emergence of labor market institutions that protected workers. Labor law, first drafted under French rule in the beginning of the nineteenth century, prohibited collective bargaining over wages or working conditions. Employers did not recognize labor unions as legitimate partners in collective bargaining until after the First World War (Luyten 1995). Chlepner (1972, 27) describes Belgian labor unions in the nineteenth century as follows: *"It is not necessary to describe at length what does not exist"*. Labor unions were not only nonexistent, but labor contracts were also informal and predominantly verbal, with minimal legal costs associated with hiring and firing (Van den Eeckhout 2005). Child labor, working time, and factory inspection were also less regulated in Belgium than in most European countries in the nineteenth century (Huberman and Lewchuk 2003).

This paper argues that, despite the lack of formal institutions supporting workers, average real wages started to grow and wage inequality decreased because the balance of power shifted in favor of workers due to changes in overall labor market conditions. In particular, the widespread adoption of steam engines increased aggregate labor demand and increased the relative wages of low-wage workers, as predicted by our model.

4. Data

4.1. The Industrial Censuses of 1846 and 1896

This paper builds on two comprehensive industrial surveys performed by the Belgian government, digitized by us. The first industrial census of Belgium was performed on 15 October 1846 by Adolphe Quetelet. The ambition and scale of this project was unlike any other census before. A questionnaire was distributed to every taxable entrepreneur who "*by himself or by wage laborers under him, makes any kind of manipulation to a raw material or a product, and gives them, by his work, a greater value*" (Statistique de la Belgique 1846, VIII). Through this process, wages were collected from 314,842 employees. The results for each of 19 industries were published in tables for each of 40 geographical districts, along with information on employment, the use of steam engines measured in horsepower efficiency units.

On the 50th anniversary of the first industrial census, the Belgian government launched a second industrial census covering all 19 manufacturing industries. The 1896 Industrial Census surveyed all entrepreneurs "*who, by means of his own tools, operates the transfer, preparation or production of any goods, either alone or with the assistance of salaried employees by him, and who works for the consumer*" (Office du Travail 1896, 12). Two complementary measures were taken. Small firms received an additional form in which they were asked to list their employees by professional categories and according to their wage. The payrolls of all enterprises with more than 10 to 20 employees were manually consulted by agents who were tasked to secure the wages of each individual worker. In total, 612,892 wages of 671,511 workers were successfully collected. Like in 1846, comprehensive counts of the amount of steam-engine horsepower installed in each of 19 sectors in each of 41 districts are also available.[17] Combined with the 1846 census data, this gives us industry-district-time variation in employment, wages, and a comparable measure of technology adoption.[18]

Because historical statistics on female employment and wages are contentious (for example, see Humphries and Sarasúa 2012), we present evidence using the sample of male workers only in our empirical analyzes below. The same analyzes that use the sample of male and female workers are qualitatively identical and are referred to the appendix.[19] Finally, it is important to note that our employment and wage data cover all manufacturing workers. Our data do not rely on the construction of wage indices based on representative occupations as in earlier historical work (Scholliers 1995; Segers 2003). Furthermore, the fine-grained geographical and industrial composition of our data allows us to investigate the relationship between steam-based industrialization and relative wage changes accounting for industry-district fixed effects, or to instrument

[17] The 1846 census contains information for 41 districts, whereas the 1896 census contains more granular information for 2,607 communities for some variables. At the district level, the 1896 census sometimes does not distinguish between the adjacent districts of Charleroi and Soignies. Therefore, we aggregated both the 1846 and the 1896 data to the level of 40 districts, merging the Charleroi and Soignies districts.

[18] See Appendix C for details. Historians generally regard these two censuses as highly comparable (De Brabander 1984, 75; Scholliers 1991).

[19] Both industrial censuses also contain information on child labor. However, the reliability and coverage of these data are extra difficult to gauge. Furthermore, child labor is one of the few cases for which the Belgian government - from 1889 onward - imposed some institutional restrictions, although the country was notoriously late in regulating child labor (De Herdt 1996; Huberman and Lewchuk 2003). For these reasons, we omit child labor in our analyzes.

the adoption of steam power with exogenous geographical variation.

4.2. Steam power

Our data contain information on the industrial use of steam engine horsepower for each of 40x19 industry-district cells in 1846 and 1896. Figure 3 illustrates the widespread adoption of steam power between 1846 and 1896. Panel (A) shows the adoption of steam engines in all industries. In 1846, the use of steam engines was strongly concentrated, with more than half of total horsepower installed in coal mining, textiles and iron & steel. The use of steam engines in other sectors was very limited. In 1846, barely 1% of all Belgian firms had adopted steam engines of some kind (Van Neck 1979, 780). However, in the fifty years that followed, the use of steam engines spread to all but a few manufacturing industries. In food processing, sugar refineries, milling and the drinks industry (breweries and distilleries) adopted mechanized production techniques.[20] Steam engines were also increasingly adopted in the chemicals industry, usually considered the hallmark pioneer of the Second Industrial Revolution, where mechanization was carried out by advances in the industrial application, production and processing of mineral resources (such as cokes) and chemicals (such as soda).

Panel (B) of Figure 3 illustrates the adoption of steam power between 1846 and 1896 in all 40 districts. In 1846, the use of steam engines was concentrated in the coal-rich districts of Wallonia, primarily Charleroi, Namur and Liège, which were the first places on the European continent to adopt the Newcomen engine, invented by Thomas Newcomen in 1712, to pump water out of coal mines, allowing miners to extract coal from deeper areas previously flooded (Lebrun et al. 1981, 263). However, between 1846 and 1896, the use of steam engines spread to the more peripheral areas around Belgium's industrial base. In general, Figure 3 illustrates the spread of steam power across sectors and districts as a general purpose technology (GPT).

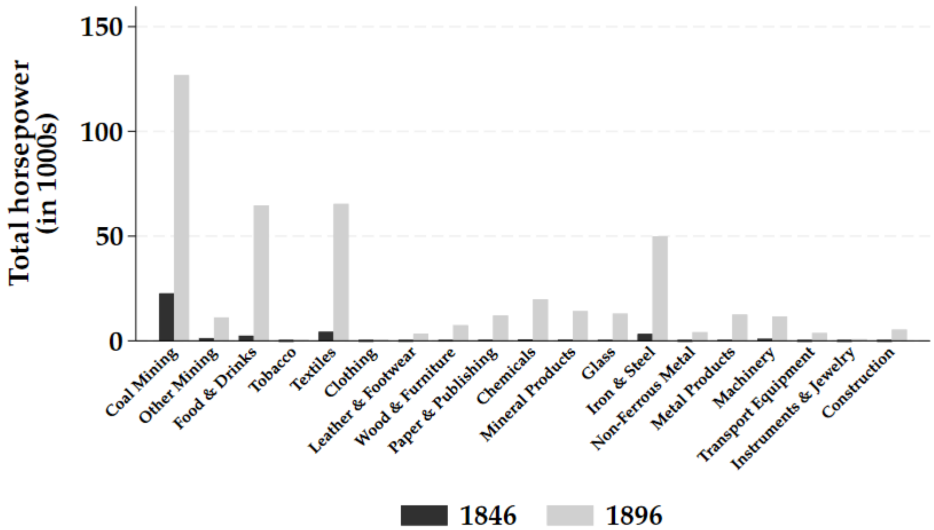
4.3. Daily wages

Our data also contain wage information for factory workers in each industry-district cell in 1846 and 1896. The wage information in the Industrial Censuses is published in

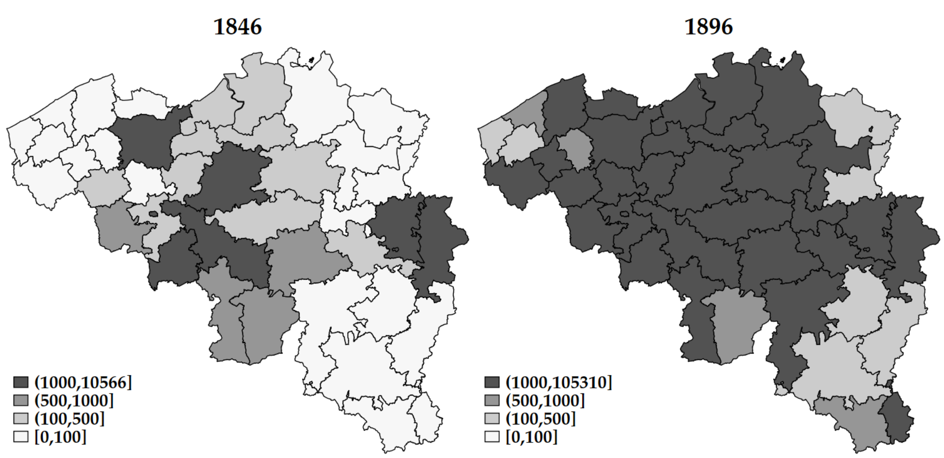
[20]For example, under increasing population pressure and high levels of beer consumption, steam engines revolutionized beer production. Initially used to mill grain and pump liquids, steam power was later applied to various processes such as mixing, heating, and cleaning, significantly increasing efficiency and scale (Van der Hallen 2011, 227-235).

FIGURE 3. Evolution of steam engine horsepower usage, 1846-1896

A. By industry



B. By district



Source: authors' database (see text).

an interval-censored form: the data sheets assign each worker's unobserved wage w_i to an observed wage interval $[w_i^l, w_i^h]$. All wages have been deflated using the CPI of Segers (2003, 622), and are expressed in 1910 Belgian Francs (BEF).[21]

Figure 4 illustrates this for the spinning of hemp fibers in textiles. Cultivated in local fields, cut hemp stalks were transported to spinning factories. There, the hemp fiber was first separated from the woody core of the stalks, which could be done by hand or with the help of a special decortication machine. Using spinning machines, the fibers were then twisted together to form hemp threads, which were sold to weaving factories that produced textiles. The figure shows an extract from the 1896 data sheets, listing all districts in Belgium with hemp spinning plants.[22]

The last row of Figure 4 shows that for Belgium as a whole, there were five spinning factories that employed a total of 156 workers. The first to second last rows show that these spinning factories were located in the Saint-Nicolas and Termonde districts.[23] For example, the first row contains data from a single factory in Saint-Nicolas that employed 127 workers in 1896, of which 101 were older than 16 years. Of these 101 adult workers, 39 were men and 62 were women. Among the 39 men, 23 earned less than 1.5 BEF for an 11-hour workday operating spinning machines. Another 12 men spun threads by hand and earned a piece-rate wage between 2.5 and 3 BEF during an average 11-hour day. The 4 remaining men provided non-production tasks, with a driver earning between 2 and 2.5 BEF per day, a carpenter and a machinist with daily wages between 2.5 and 3 BEF, and a mechanic earning between 3.5 and 4 BEF per day. The 62 adult women were all employed in the preparatory stages of separating the fiber from the cut hemp stalks, and they were paid between 1 and 1.5 BEF for an 11-hour workday.

We digitized data sheets for all industries and districts in 1846 and 1896, and used two approaches to construct relative daily wages. In a first approach, we simply assign midpoints of bins to all workers in that bin (i.e. assuming a uniform distribution within every wage category). That is, $\forall i : w_i = [w_i^l + w_i^h]/2$. We then compute wage percentiles, using the number of workers in each bin as weights. This allows us to measure wage inequality in each of industry-district cell in 1846 and 1896. However, one shortcoming of this approach is that assigning the same midpoint wage to all workers in the same bin,

[21] 1 Belgian Franc in 1910 is about 1 US Dollar today.

[22] See Appendix D.1 for an example of a data sheet from the 1846 Industrial Census.

[23] Each district is listed twice because the 1896 (but not the 1846) data sheets report a separate row for each factory employing more than 10 workers.

FIGURE 4. Wages and employment in the Industrial Census of 1896

CADRE XI. — 2 — — 3 — CADRE XI.

N. B. — *Dans ce cadre, on a présenté comme entreprises distinctes les divisions industrielles des entreprises qui en comprennent plusieurs.*

ENTREPRISES ET DIVISIONS D'ENTREPRISES EN ACTIVITÉ OCCUPANT DES OUVRIERS ÉTRANGERS A LA FAMILLE DES EXPLOITANTS.

Répartition du personnel ouvrier d'après le taux des salaires.

N. B. — *Dans ce cadre, on a présenté comme entreprises distinctes les divisions industrielles des entreprises qui en comprennent plusieurs.*

N. B. — Les taux des salaires ont été établis d'après les livres de paie des chefs d'entreprise, pour la dernière paie qui a précédé le recensement; ils représentent non des moyennes, mais le revenu réel d'une journée normale de travail pour chaque ouvrier et ouvrière à la fin du mois d'octobre 1896.

Numéro d'ordre. (1)	Exploitations industrielles et métiers. (2)	Situation des entreprises et divisions d'entreprises. (3)	Nombre considéré d'entreprises en activité. (4)	Personnel ouvrier des entreprises considérées. (5)	Nature du travail effectué. (6)	Catégories d'ouvriers par spécialités de travail [non compris les contremaîtres, porions, surveillants, etc.]. (7)	Mode de rémunération T : au temps. [hre: heure; — jée: journée, — sem.: semaine, — qne: quinzaine]. — P : à la pièce, à la quantité. [ind.: individuellement, — coll.: collectivement.] (8)	Moins de 16 ans — Garçons — Nombre d'heures de travail par jour [repos déduits] (9)	Garçons — Total (10)	Garçons — ayant gagné par jour moins de 0.50 fr. (11)	Garçons — de 0.50 à 0.99 fr. (12)	Garçons — de 1.00 à 1.49 fr. (13)	Garçons — 1.50 fr. et plus. (14)	Filles — Nombre d'heures de travail par jour [repos déduits] (15)	Filles — Total (16)	Filles — ayant gagné par jour moins de 0.50 fr. (17)	Filles — de 0.50 à 0.99 fr. (18)	Filles — 1.00 fr. et plus. (19)
	INDUSTRIES TEXTILES. — Fabrication des fils et des tissus de chanvre et de jute.																	
4450	**Chanvre** (*filatures mécaniques de*).	ARRONDISSEMENT DE St-NICOLAS. 1 petite ville.	1	127	FABRICATION.	Dévideuses	P.—ind.	—	—	—	—	—	—	11	2	—	—	2
						Fileuses	T.—hre.	—	—	—	—	—	—	—	—	—	—	—
						id. (aides)	T.—hre.	—	—	—	—	—	—	11	12	—	12	—
						Ouvrières de préparation	T.—hre.	—	—	—	—	—	—	11	5	—	5	—
						Peigneurs à la main	P.—ind.	—	—	—	—	—	—	—	—	—	—	—
						id. à la machine	T.—hre.	11	7	—	7	—	—	—	—	—	—	—
					SERVICES GÉNÉRAUX.	Charpentier	T.—hre.	—	—	—	—	—	—	—	—	—	—	—
						Chauffeur	T.—hre.	—	—	—	—	—	—	—	—	—	—	—
						Machiniste	T.—hre.	—	—	—	—	—	—	—	—	—	—	—
						Mécanicien	T.—hre.	—	—	—	—	—	—	—	—	—	—	—
4451	**Chanvre** (*filatures mécaniques de*).	ARRONDISSEMENT DE St-NICOLAS. 1 petite ville.	1	5	FABRICATION.	Fileurs	T.—jée.	11½	2	—	—	2	—	—	—	—	—	—
						Retordeurs	T.—jée.	—	—	—	—	—	—	—	—	—	—	—
4452	**Chanvre** (*filatures mécaniques de*).	ARRONDISSEMENT DE TERMONDE. 1 grosse commune.	1	13	FABRICATION.	Bobineurs	P.—ind.	12	1	—	1	—	—	—	—	—	—	—
						Fileurs	P.—ind.	—	—	—	—	—	—	—	—	—	—	—
4453	**Chanvre** (*filatures mécaniques de*).	ARRONDISSEMENT DE TERMONDE. 1 grosse commune.	2	11	FABRICATION.	Fileurs	T.—jée.	—	—	—	—	—	—	11½	3	—	—	3
						Séranceurs	T.—jée.	—	—	—	—	—	—	—	—	—	—	—
	Chanvre (*filatures mécaniques de*).	LE ROYAUME.	5	156	TOTAUX GÉNÉRAUX.		—	—	10	—	8	2	—	—	22	—	17	5

Numéro d'ordre. (1)	Catégories d'ouvriers (7)	Plus de 16 ans — Hommes — Nombre d'heures de travail par jour [repos déduits] (20)	Hommes — Total (21)	Hommes — ayant gagné par jour moins de 1.50 fr. (22)	de 1.50 à 1.99 fr. (23)	de 2.00 à 2.49 fr. (24)	de 2.50 à 2.99 fr. (25)	de 3.00 à 3.49 fr. (26)	de 3.50 à 3.99 fr. (27)	de 4.00 à 4.49 fr. (28)	de 4.50 à 4.99 fr. (29)	de 5.00 à 5.49 fr. (30)	de 5.50 à 5.99 fr. (31)	de 6.00 à 6.49 fr. (32)	de 6.50 à 6.99 fr. (33)	7.00 fr. et plus. (34)	Femmes — Nombre d'heures de travail par jour [repos déduits] (35)	Femmes — Total (36)	Femmes — ayant gagné par jour moins de 1.00 fr. (37)	de 1.00 à 1.49 fr. (38)	de 1.50 à 1.99 fr. (39)	de 2.00 à 2.49 fr. (40)	de 2.50 à 2.99 fr. (41)	de 3.00 à 3.49 fr. (42)	de 3.50 à 3.99 fr. (43)	4.00 fr. et plus. (44)	Moins et plus de 16 ans, ayant gagné par jour une somme dont le montant n'a pu être déterminé — Garçons (45)	Filles (46)	Hommes (47)	Femmes (48)	Total (49)
4450	Dévideuses	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	11	15	—	15	—	—	—	—	—	—	—	—	—	—	—
	Fileuses	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	11	27	—	27	—	—	—	—	—	—	—	—	—	—	—
	id. (aides)	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	Ouvrières de préparation	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	11	20	—	20	—	—	—	—	—	—	—	—	—	—	—
	Peigneurs à la main	11	12	—	—	—	12	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	id. à la machine	11	23	23	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	Charpentier	11	1	—	—	—	1	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	Chauffeur	11	1	—	—	1	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	Machiniste	11	1	—	—	—	1	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	Mécanicien	11	1	—	—	—	—	—	1	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
4451	Fileurs	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	Retordeurs	11½	3	—	—	—	3	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
4452	Bobineurs	12	4	—	2	1	1	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	Fileurs	12	6	—	2	2	2	—	—	—	—	—	—	—	—	—	12	2	—	—	1	1	—	—	—	—	—	—	—	—	—
4453	Fileurs	12	3	—	—	3	—	—	—	—	—	—	—	—	—	—	11½	3	—	3	—	—	—	—	—	—	—	—	—	—	—
	Séranceurs	11½	2	—	—	2	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	TOTAUX GÉNÉRAUX.	—	57	23	4	9	20	—	1	—	—	—	—	—	—	—	—	67	—	65	1	1	—	—	—	—	—	—	—	—	—

Source: Office du Travail (1896), volume XII, pages 2-3 as well as having to make assumptions on the open-ended wage category $\{w_i^H, \infty\}$[24], are likely to introduce noise in our wage measures. As long as this error is exogenous to our independent variable of interest, however, this is unlikely to affect our coefficients of interest.

Be that as it may, we also propose a second approach in which we impute wage percentiles by parametrically estimating wage densities using Maximum Likelihood (see McDonald and Ransom 2008; Hlasny 2021). For the functional form, we estimate three parameters to fit a continuous Dagum probability density function (Dagum 1977).[25] Fitting a continuous Dagum density results in wage variation even within observed wage bins, which is more realistic. However, one drawback of this approach is that the likelihood function does not always converge to a maximum if there are insufficient observations in the wage bins. Therefore, we only impute wage percentiles at the more aggregate industry-province (instead of industry-district) level. Because the 40 districts can be grouped into nine provinces, we estimate smooth wage densities for 19x9 industry-province cells. We refer to Appendix D.2 for more details on this approach, as our regression results in the main text will be estimated through the first approach.

5. Changes in wage inequality

To assess whether changes over time in overall wage inequality were mainly the result of workers shifting between industries or provinces, or whether changes occurred largely within each industry or province, we re-weight the importance of industry-province employment in the overall wage density of 1896 by their employment shares in 1846 following the method by DiNardo, Fortin, and Lemieux (1996). That is, we ask the question: what would overall wage inequality be in 1896 in a counterfactual world in which employment shares across industry-province cells would not have changed but wages would have grown within each industry-province as they did between 1846 and 1896? If this counterfactual density for wages in 1896 is close to the actual wage density for 1896 but not for 1846, it must be that the change in overall wage inequality is mainly driven by changes within rather than between industry-province cells. Panel A

[24] For this wage category, we simply extrapolate the wage midpoints from the lower wage categories.

[25] The Dagum distribution is commonly used in studies estimating the income distribution. Other examples assuming this distribution are (Bandourian, McDonald, and Turley 2003; Kleiber 2008; Von Hippel, Scarpino, and Holas 2016; Hlasny 2021). Our results are robust to fitting other three- and four-parameter distributions, such as a Singh–Maddala (Singh and Maddala 1976) or a GB2 (McDonald 1984) distribution.

of Figure 5 shows that this is indeed the case. Although there was some reallocation towards better-paying industries and districts, relative wage changes mostly occurred within industries and provinces.

Panel B of Figure 5 further illustrates how wage inequality changed within industry-province cells between 1846 and 1896. The gray lines plot wage growth by percentile in each industry and province, and the black line shows growth in overall wage percentiles. Importantly, lower-wage percentiles grew faster within most industry-province cells, resulting in an overall compression of lower-tail wage inequality. An interesting question is whether the widespread adoption of steam engines is an important driver of these changes. To answer this question more causally, the next section exploits the variation in changes over time in relative wages within industry-province cells documented in Figure 5 by relating it to the variation in changes over time in the adoption of steam engines within industry-province cells.

6. Empirical results

6.1. Two-Way-Fixed-Effects (TWFE) estimates

Consider the following regression equation:

$$\ln Y_{idt} = \alpha + \gamma D_{1896} + \beta \ln STEAM_{idt} + F_{id} + \epsilon_{idt} \tag{17}$$

with Y_{idt} a wage percentile in industry i, district (or province) d, at time t. The variable D_{1896} is a time dummy equal to 1 for 1896, and $STEAM_{idt}$ captures the use of steam engines measured in horsepower per worker in industry i and district d at time t. The term F_{id} is a vector of industry-district dummies, and ϵ_{idt} is an error term. First-differencing Equation (17) over time gives an alternative estimating equation:

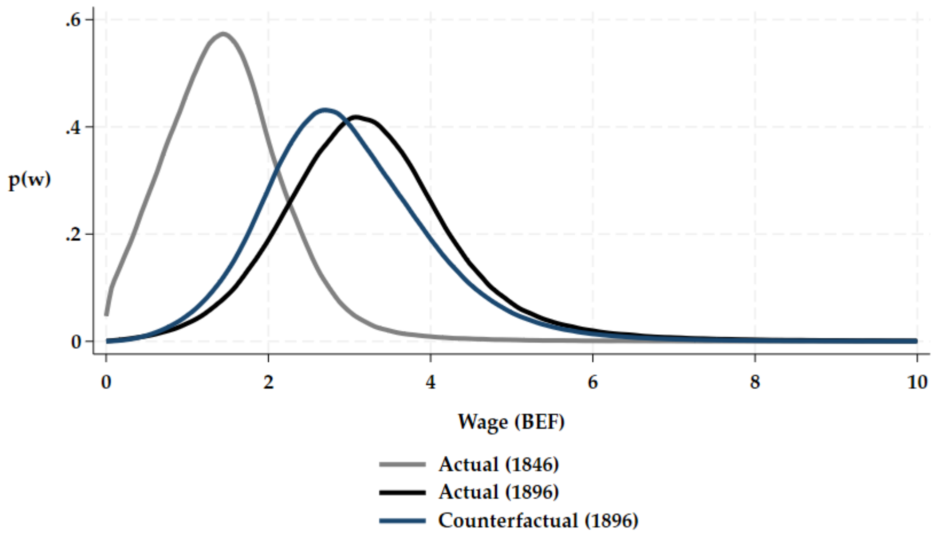
$$\Delta \ln Y_{id} = \gamma + \beta \Delta \ln STEAM_{id} + \Delta\epsilon_{id} \tag{18}$$

We are most interested in estimates of γ and β. Estimates of γ capture the growth of a wage percentile between 1846 and 1896 that is common across industries and districts, and estimates of β capture the impact of industry-district-specific growth of steam power on the growth of a wage percentile in that industry and district. Given our model, we expect that γ and β are larger for lower wage percentiles.

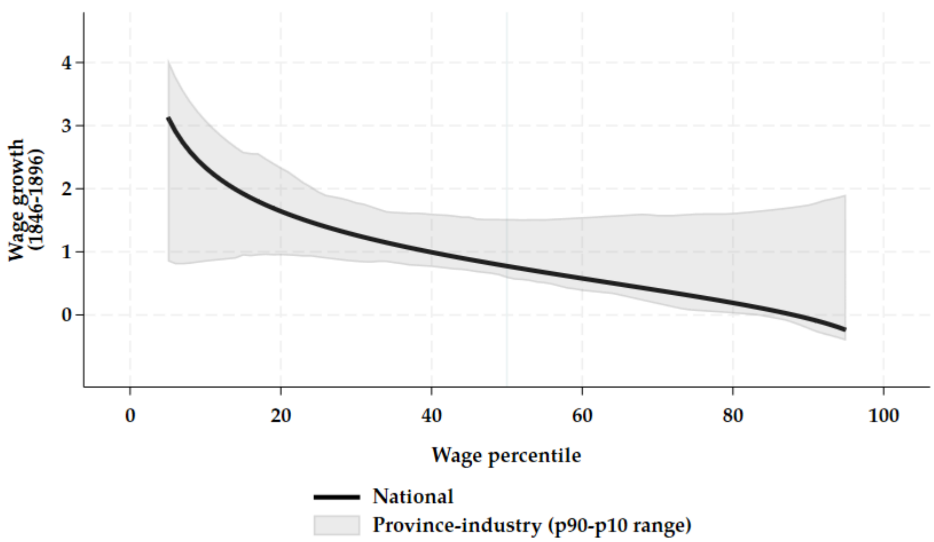
Different definitions of Y_{idt} can be used. Panel A of Figure 6 uses the midpoint

FIGURE 5. **Changes in relative daily wages, 1846-1896**

A. Actual and counterfactual wage distributions



B. Wage growth by percentile



Notes: Panel (A): The actual distributions are fitted to the grouped wage data using a Dagum (1977) functional form. The counterfactual distributions are simulated using the approach by DiNardo, Fortin, and Lemieux (1996). Panel (B): The gray area shows the $p90$ and $p10$ of wage growth over all industry-province cells, for every wage percentile.

bin measures to impute wage percentiles in each industry-district cell in 1846 and 1896.[26] Each imputed percentile is then used separately to estimate Equation (17), and the percentile-specific point estimates for γ and β are plotted for each value on the horizontal axis of panel A of Figure 6. Estimates of the time-fixed effects show that percentiles 1,5 and 10 grew about 70%, while percentiles 90, 95 and 99 grew about 50% on average across all industry-district cells. Estimates of the impact of industry-district-specific adoption of steam engines indicate that doubling steam power per worker increased lower wage percentiles by approximately 20%, and higher wage percentiles by approximately 5%. Panel B of Figure 6 defines Y_{idt} as a wage percentile relative to the median, and finds positive estimates for percentiles below the median and negative estimates for percentiles above the median. These estimates suggest that technological progress resulted in average wage growth, as well as a compression in lower-tail wage inequality.

6.2. Instrumental Variables (IV) estimates

However, the estimates in Figure 6 could not capture the causal effect of technological progress on wages. To address this concern, this section uses an IV design.

6.2.1. Using potential hydropower and coal deposits as instruments

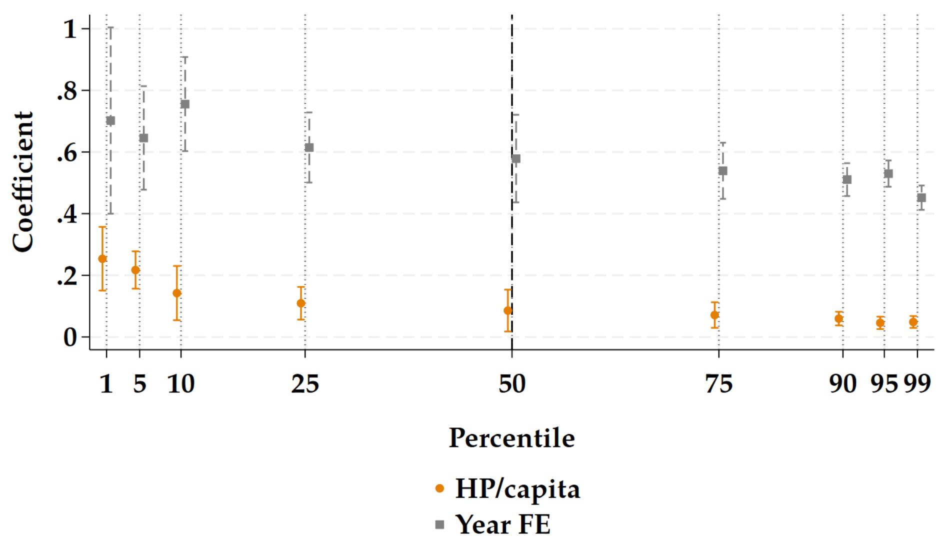
We instrument $\Delta \ln STEAM_{id}$ in Equation (18) using two instruments. First, we instrument the growth in horsepower per worker between 1846 and 1896 with a district's potential for the generation of hydropower. Economic historians have documented the extensive use of water power in the British Industrial Revolution (Musson 1976), and it has been suggested that the efficacy of water power delayed the adoption of steam-based technologies (Mokyr 1990, 90). In addition, studies of the American Industrial Revolution have underlined the impeding role of lower costs of water power in the transition to new steam-based technologies (Atack, Bateman, and Weiss 1980; Hornbeck et al. 2023).[27]

[26] Estimates including adult women and/or using maximum likelihood imputations of wage percentiles are qualitatively identical. See Appendix F for details.

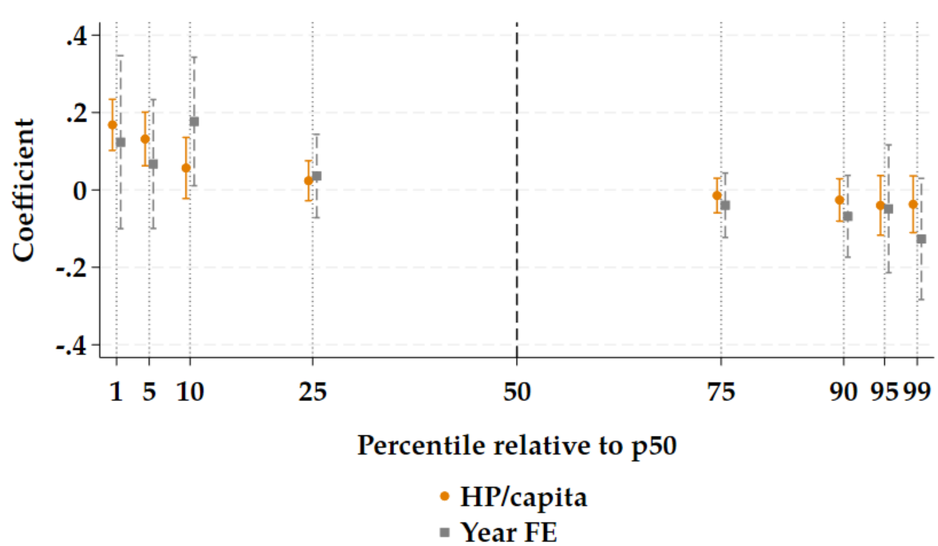
[27] In some cases, owners of traditional water and wind mills actively opposed the adoption of new steam technologies. For example, in a 1841 letter, a public official of the district of Roeselare warned the governor of the province of West Flanders of *"the harm that will result from the establishment of a steam engine for the owners of mills"* (Van Neck 1979, 174). However, the prevalence and impact of these protests are considered limited, both in Belgium (Van Neck 1979, 169) and internationally (Mokyr 2002, 256).

FIGURE 6. OLS estimates of γ and β, industry-district level

A. Wage percentiles



B. Wage percentiles relative to the median



Notes: The regressions are weighted using the employment shares. Clustered standard errors at the district level. More details can be found in Table F1 (panel A) and Table F2 (panel B) in Appendix F.2.

These insights suggest the use of the potential of a district to generate hydropower as a valid instrument for the adoption of steam technologies. Therefore, we measure the hydropower potential of a district using a current-day database that identifies viable areas for hydropower generation (Hoes et al. 2017), from which we calculate the density of potential water mill locations per district in our historical data. Although we use a current-day measure for an area's potential to generate hydropower, this measure strongly correlates with the use of watermills in 1846 which we observe in our historical data.[28] Panel A of Figure 7 shows the relevance of the potential of a district to generate hydropower as an instrument in the first stage.[29] A negative correlation suggests that the potential of hydropower (and the use of watermills in 1846) is a substitute for the adoption of steam power.[30]

Second, we also instrument the adoption of steam power at the district level by the presence of local coal deposits, an approach that has also been used in other papers (De Pleijt, Nuvolari, and Weisdorf 2020; Esposito and Abramson 2021; Ridolfi, Salvo, and Weisdorf 2023; Reichardt 2025). More specifically, we quantify local coal deposits using the historical atlas data from Atlas Châtel & Dollfus (1931) and Esposito and Abramson (2021).[31] We merge this information into our historical data by constructing a measure of the share of the surface of a district that potentially contains coal deposits. Panel B in Figure 7 summarizes the relevance of this instrument for the first stage, suggesting a negative correlation.[32] Our intuition for this negative correlation is that the proximity to coal deposits became much less important due to the expansion of railways, which allowed districts with fewer coal deposits to also adopt steam engines. In 1846, the Belgian railroad network was still in its infancy. However, by 1896, the Belgian railways had become the densest network in the world, connecting all districts (O'Brien 1983; Martí-Henneberg 2013).

[28] See Figure G1 in Appendix G for details.

[29] The Kleibergen-Paap F statistic is 58. See Appendix G.1 for details.

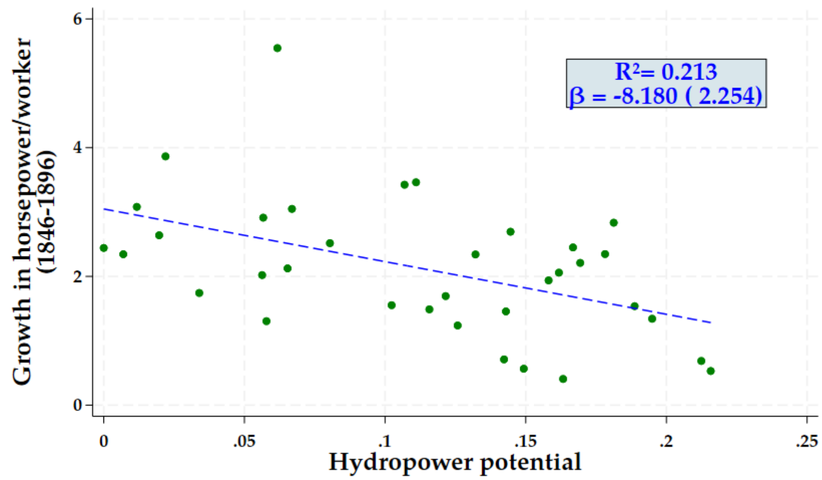
[30] This is not necessarily always the case, however. For example, steam engines were sometimes installed to complement existing water mills. Perhaps the most convincing evidence for the complementary nature of steam engines and water mills is provided by Ashraf et al. (2024), who find a positive relationship between the initial use of water mills and the subsequent adoption of steam engines in 19th-century Prussia.

[31] We thank Elena Esposito for sharing this information.

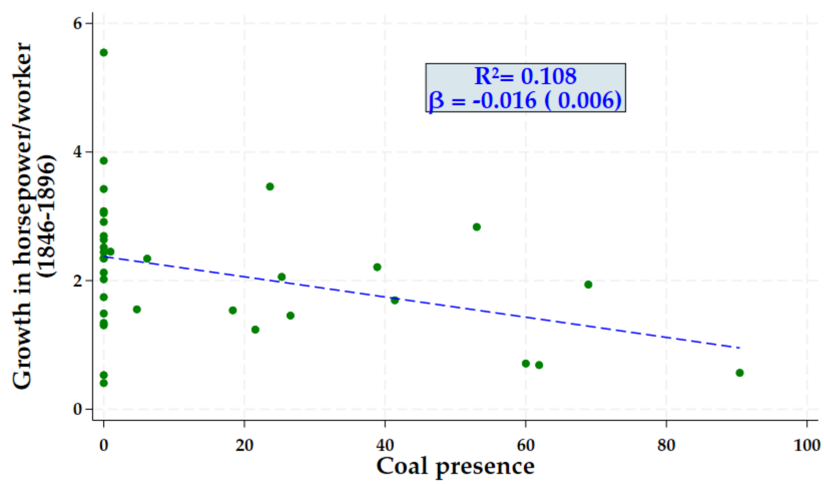
[32] The Kleibergen-Paap F statistic is 91. For the over-identified model using both instruments simultaneously, the Kleibergen-Paap F statistic is 99.

FIGURE 7. **Relevance of instruments, district level**

A. Hydropower potential and changes steam power adoption, 1846-1896



B. Coal deposits and changes steam power adoption, 1846-1896



Notes: Panel (A): Hydropower potential is calculated as the number of potential hydropower locations per km^2 within a district. Panel (B): Coal presence is calculated as the share of surface within a district covered by coal surfaces.

6.2.2. IV estimates of β

IV estimates of Equation (18) are consistent only if our instruments are relevant and valid. Relevance was already documented in the previous subsection. The more challenging identifying assumption is the validity of the instruments. Although potential hydropower and coal deposits are measures that depend only on the geographical characteristics of a district and are therefore as good as randomly assigned, each of our instruments could still violate an exclusion restriction. For example, our estimates for growth in low wages would be upward-biased if the relative demand for low-wage workers increased for other reasons than the adoption of steam power, and more so in districts where the potential for hydropower and the presence of coal deposits are lower. In the following sections, we provide evidence that such alternative explanations are not very important. In this section, we test for instrument validity showing that we cannot reject the null hypothesis that our instruments are valid.

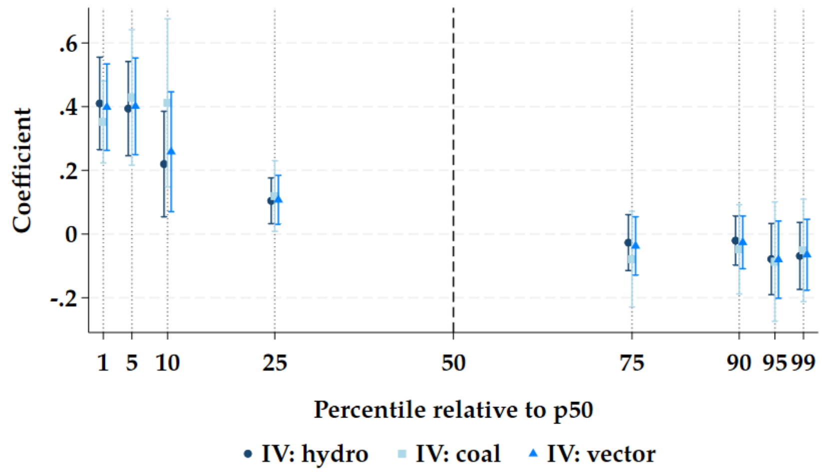
Panel A of Figure 8 shows the IV estimates of β using Equation (18), while defining Y_{idt} as the wage percentile relative to the median. For each percentile, we plot the estimates for the exactly identified models using a single instrument, as well as for the over-identified model using both instruments simultaneously. Point estimates are very similar for exactly and over-identified models, suggesting a homogeneous impact of steam power on relative wages across the different instruments. Assuming effects are truly homogeneous, the over-identified model has a Hansen J statistic of 0.1 with a p-value of 0.75, such that the null hypothesis that our instruments are valid cannot be rejected. Also note that for each wage percentile, its IV estimates are higher than its OLS estimates in panel B of Figure 6. In sum, our 2SLS estimates are consistent with the predictions of our model of monopsony-reducing technological change.

6.3. Did the relative supply of low-wage workers decrease?

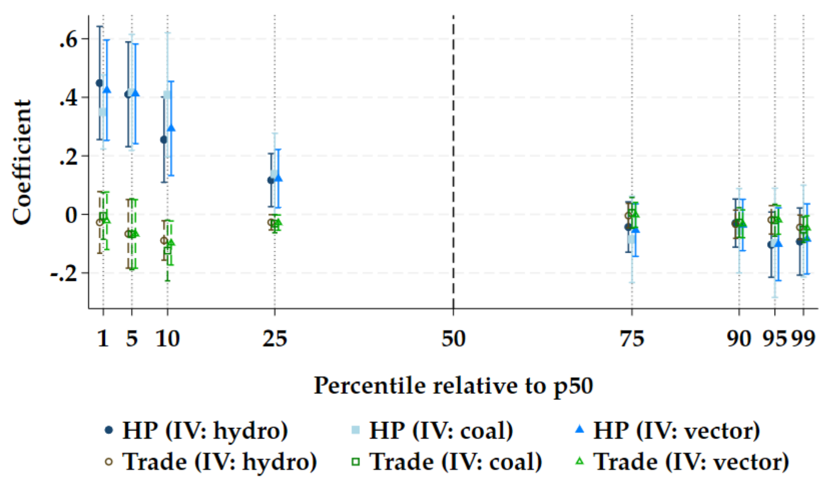
The remaining key question is whether the results of Sections 6.1 and 6.2 can be interpreted by the effects of technological change on the aggregate labor demand, as stipulated by our model in Section 2. We see two main threats to our interpretation. First, the documented relationship between mechanization and wage inequality could be explained away by a decrease *supply* in the supply of low-wage workers relative to high-wage workers. Second, the unskilled-biased nature of trade and technological progress increased the demand for low-wage workers relative to high-wage workers. This subsection examines the possibility that the relative supply of low-wage workers

FIGURE 8. **IV estimates of β, industry-district level**

A. Using Equation (18)



B. Augmenting Equation (18) with exports per worker



Notes: The regressions are weighted using the employment shares. Clustered standard errors at the district level. More details can be found in Table G3 (panel A) and Table G4 (panel B) in Appendix G.3. The first-stage estimates can be found in Table G1 in Appendix G.1.

has decreased. Section 7 will focus on alternative explanations for an increase in the relative demand for low-wage workers.

The relative wage of low-wage workers could have increased if steam-based industrialization induced a relative withdrawal of low-wage workers from the labor market. This could, for example, have been the result of the demographic transition that unfolded in the latter decades of the nineteenth century in Belgium (Lesthaeghe 1977, 101-105). Lower levels of fertility that spread to lower levels of society could have decreased the relative supply of low-wage workers. In addition, income growth could have changed gender norms and societal expectations surrounding work and family such that women retreated from (formal) labor markets.[33]

However, it is more likely that the relative supply of low-wage workers to manufacturing jobs increased rather than decreased. Scholliers (1991, 114) observed that "*wage inequality decreased, precisely at the moment that a large supply of labor was released from the agricultural sector*". He concluded that, therefore, the mechanization of manufacturing must be the main explanation for the decrease in wage inequality. In addition, other studies have found that agricultural employment declined in the second half of the 19th century due to an increase in grain imports from the United States, as well as an increase in agricultural productivity, providing a continuous supply of labor to manufacturing jobs (Blomme 1993; Buyst Forthcoming). For example, there is some direct evidence that negative wage shocks in agriculture resulted in higher levels of labor supply for Belgian coal mines (Delabastita and Rubens 2025).

To provide some further evidence to support the hypothesis that the relative supply of low-wage workers to manufacturing jobs increased instead of decreased, we enrich our data with information about agricultural employment at the district level in 1846 and 1896.[34] Figure 9 then visualizes the correlation, for both 1846 and 1896, between a district's manufacturing employment share (as a fraction of total employment in agriculture and manufacturing) on the vertical axis and a district's steam engine horsepower per worker on the horizontal axis. In both years, this correlation is positive, suggesting that districts with more steam engines per worker also have higher employment shares in manufacturing. This suggests that low-wage agricultural workers were drawn

[33] However, this explanation seems less likely for the time period we examine. For example, the status of *ménagère* (housekeepers) was only reserved for a small elite even in the wealthy textile district of Verviers (Alter 1988, 98). Overall, it has been shown that women increased their labor force participation in 19th-century Belgian districts where female employment opportunities were abundant (Buyst and Delabastita 2023).

[34] See Appendix C.3 for details.

into low-wage manufacturing jobs due to industrialization. Moreover, the comparison between 1846 and 1896 shows that the reallocation of workers from agriculture to manufacturing strengthened between both years. These findings are in line with other studies showing that agricultural workers could increase their wages by moving into manufacturing, even though they brought little human capital or experience to the factory floor (Scholliers 1995, Segers 2003, 339).

7. Did the relative demand for low-wage workers increase?

7.1. Unskilled-biased international trade

In 1846, Belgium's trade with other regions was limited. However, because of its central location, international trade increased during the globalization wave of the second half of the nineteenth century. By 1896, Belgium was a large exporter of a highly diversified set of goods (Huberman, Meissner, and Oosterlinck 2017). Therefore, trade could be an alternative demand-side explanation for the observed changes in the wage distribution if trade were biased in favor of low-wage workers.

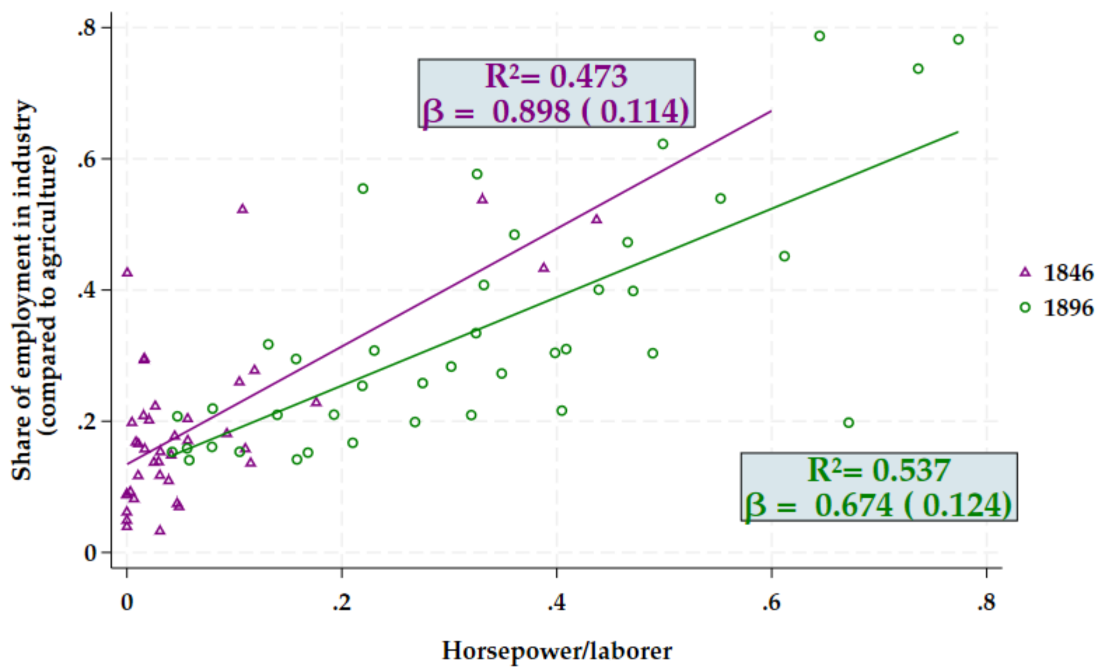
To assess the importance of unskilled-biased trade, we collected data on trade volumes to document the industrial composition of the export boom of Degrève (1982).[35] We then augment Equation (18) with a district's growth in exports per worker and re-estimate it using both instruments simultaneously. Panel B of Figure 8 summarizes the point estimates: we do not find any relationship between the growth of exports per worker and the changes in relative wages, with the trade coefficients being insignificant in all specifications except for the 99th percentile. However, the estimates of β remain unchanged.

7.2. Unskilled-biased technological change

Our estimates of β could also be consistent with the "de-skilling hypothesis" (Katz and Margo 2014, 42). According to this view, steam technology is more complementary for unskilled workers than for skilled workers. Consequently, the demand for unskilled relative to skilled workers increases, resulting in a fall of the skill premium. The evidence

[35] The Belgian trade statistics were published at product level. We coded these products in *Standard International Trade Classification* (SITC revision 2) and linked them to the ISIC (revision 2) codes in our main data, using the concordance table provided by Muendler (2009). See Appendix C.2 for details.

FIGURE 9. Manufacturing employment shares and steam power adoption, district level



Notes: The vertical axis is calculated using total agricultural and industrial employment from the agricultural and industrial censuses, respectively. For more information on agricultural employment data, we refer to Appendix C.3.

for the US seems to be largely supportive of this hypothesis: Lafortune, Lewis, and Tessada (2019) deduce from the Age of Mass Migration that technological change was biased toward unskilled labor. In addition, Atack, Bateman, and Margo (2004) and Katz and Margo (2014) provide evidence that is broadly supportive of the deskilling hypothesis.

However, in a careful review of the literature, Bessen (2012) argues that evidence on the skill effects of mechanization in American 19$^{\text{th}}$-century manufacturing is mixed. The evidence for European countries is also mixed. On the one hand, some studies find that occupational wage differences were stable throughout much of the 19$^{\text{th}}$ century (Clark 2007; van Zanden 2009). However, other studies suggest that steam engines increased the demand for skilled workers compared to unskilled workers. In England, the use of steam engines resulted in higher levels of apprenticeship (Feldman and van der Beek 2016) and higher returns to experience (De Pleijt, Nuvolari, and Weisdorf 2020). Similarly, Franck and Galor (2022) have found that the adoption of steam engines increased the returns to schooling in France during the period 1839-1847.

Unfortunately, we do not have data on workers' skills.[36] But even if we did, casting a horse race between a decrease in firms' monopsony power due to skill-neutral technological progress and the unskilled-biased nature of technological change could be misguided. To see this, return to the model in Section 2 but now assume that there exist several skill types indexed by $s = 1, ..., S$. Firm-level labor supply for each skill type $s = 1, ..., S$ is then given by:

$$\ln(l_j^s) = [\epsilon(1-\epsilon_{\theta w}) - \epsilon_{\theta w}]\ln(w_j^s) + \ln(\lambda^s \tilde{L}^s) \tag{19}$$

with $\tilde{L}^s$ the total number of job applicants of skill type s. For simplicity, we assume that skill types have the same preference parameters ϵ and $\epsilon_{\theta w}$. Introducing a different utility function for skill type would not qualitatively change the analysis. Further assume that each firm $j = 1, ..., J$ has the following production function:

$$q_j = \psi_j \sum_{s=1}^{S} \alpha^s \ln(l_j^s) \tag{20}$$

[36]We hypothesize that the heterogeneous nature of earlier findings, as discussed above, might at least partly be ascribed to the difficulty of defining and measuring 'skill' or 'human capital' in a 19th-century context. See also Henderson (2024) for a historical appraisal of human capital indicators and their shortcomings in the context of industrializing England and Wales.

with α^s a skill-specific productivity parameter.

Following the derivation of Equation (12), an equilibrium expression for wages can be derived for each type of skill. Using these expressions and assuming that there are only skilled (S) and unskilled workers (U) for simplicity, the relative wage in each firm $j = 1, \ldots, J$ is given by:

$$\ln\left(\frac{w_j^S}{w_j^U}\right) = \frac{1}{(1+\epsilon)(1-\epsilon_{\theta w})}\left[\ln\left(\frac{\alpha^S}{\alpha^U}\right) - \ln\left(\frac{\lambda^S\tilde{L}^S}{\lambda^U\tilde{L}^U}\right)\right] > 0 \tag{21}$$

We assume a positive skill premium because skilled workers are sufficiently productive and/or because they are sufficiently scarce. Note that the right-hand side of Equation (21) does not depend on j, implying that the skill premium within each firm is identical.

Importantly, Equation (21) shows that the relative wage of skilled workers can decrease following unskilled-biased technological change, captured by a decrease in α^S/α^U. Alternatively, the skill premium can decrease because the labor market becomes more competitive, captured by a decrease in $\epsilon_{\theta w}$. Therefore, examining changes in skill premia over time is not necessarily a conclusive test of the unskilled-biased nature of technological progress. If skill-neutral technological progress increases the elasticity of firm-level labor supply, the skill premium could fall within each firm and, therefore, on average in the economy.[37]

8. Conclusions

This paper showed that accounting for the importance of labor relations results in a better understanding of technology-induced changes in relative wages. Because it became increasingly easy for workers to find industrial employment due to growing labor demand caused by the widespread adoption of steam power, the balance of power between firms and workers shifted in favor of workers. Consequently, firms' wage-setting power decreased and labor markets became more competitive. Because steam-based mechanization was widely adopted and was largely complementary to labor, average

[37] As before, we assume that each firm takes λ^S and λ^U as given when setting wages for skilled and unskilled workers. If all firms decrease the skill premium, λ^S/λ^U will increase, which would further decrease the skill premium. Moreover, if $\epsilon_{\theta w}$ decreases, the comparative statics in Equations (15) and (16) still hold. For example, if unskilled workers had initially sorted into low-wage firms, the decrease in the economy-wide average skill premium would be even greater because low-skilled workers will re-allocate from low-wage to high-wage firms if the elasticity of firm-level labor supply increases.

real wages grew. Moreover, lower-tail wage inequality decreased because low-wage workers saw stronger relative wage growth and disproportionately relocated from the lowest-wage towards higher-wage firms.

Our focus on Belgium's Second Industrial Revolution was motivated by Belgium's historical context. Belgium's labor markets remained largely unregulated until the early 20th century. Because there was an excess supply of workers to do manufacturing jobs, the balance of power between firms and workers initially was tilted in favor of firms. Employment contracts were informal and mainly oral. Labor law, first drafted under French rule in the beginning of the 19th century, prohibited collective bargaining over wages or working conditions. At the same time, Belgium was the first country on the European continent to industrialize, with the widespread adoption of steam-based power in manufacturing.

The empirical application of our framework was also motivated by unique data access. The uniqueness of our industrial census data made an analysis of 19th-century Belgium particularly interesting for two reasons. First, based on wage information on every manufacturing worker in 1846 and 1896, we observe wages across manufacturing sectors and geographical districts. Second, we observe the use of steam-based machinery expressed in horsepower, which gives us a unique measure of technology adoption across detailed sector-district cells. Using these data and an instrumental variables approach, we found evidence in support of our model's predictions that technological progress, in part through its impact on labor relations, resulted in average real wage growth and less wage inequality.

If labor markets are competitive and technological progress complements labor, workers' wages will increase. Another channel through which workers can benefit from productivity growth is through labor market institutions such as unions, who can negotiate higher wages. Instead, this paper has argued that wage growth can also stem from a shift in the balance of toward workers when technological progress increases labor market tightness. The idea that labor relations change depending on market conditions was a central question among economists a century ago, but it seems to have been largely forgotten in recent decades. However, it remains relevant to know whether recent changes in wage inequality could be explained by changes in the balance of power between workers and firms driven by labor shortages, or whether wages in developed countries are higher because technological progress has also created a more competitive labor market in those countries.

References

Acemoglu, Daron, and Simon Johnson. 2023. *Power and Progress: Our Thousand-Year Struggle Over Technology and Prosperity*. New York: PublicAffairs.

Acemoglu, Daron, and Pascual Restrepo. 2018. "The race between man and machine: Implications of technology for growth, factor shares, and employment." *American Economic Review* 108 (6): 1488–1542.

Acemoglu, Daron, and Pascual Restrepo. 2019. "Automation and new tasks: How technology displaces and reinstates labor." *Journal of Economic Perspectives* 33 (2): 3–30.

Acemoglu, Daron, and Pascual Restrepo. 2022. "Tasks, Automation, and the Rise in U.S. Wage Inequality." *Econometrica* 90 (5): 1973–2016.

Allen, Robert C. 2009. "Engels' Pause: Technical change, capital accumulation, and inequality in the British Industrial Revolution." *Explorations in Economic History* 46 (4): 418–435.

Alter, George. 1988. *Family and the female life course: The women of Verviers, Belgium, 1849-1880*. Madison: University of Wisconsin Press.

Armangué-Jubert, Tristany, Nezih Guner, and Alessandro Ruggieri. 2025. "Labor market power and development." *American Economic Review: Insights* 7 (2): 177–195.

Ashraf, Quamrul H, Francesco Cinnirella, Oded Galor, Boris Gershman, and Erik Hornung. 2024. "Structural Change, Elite Capitalism, and the Emergence of Labour Emancipation." *Review of Economic Studies*: rdae043.

Atack, Jeremy, Fred Bateman, and Robert A Margo. 2004. "Skill intensity and rising wage dispersion in nineteenth-century American manufacturing." *The Journal of Economic History* 64 (1): 172–192.

Atack, Jeremy, Fred Bateman, and Thomas Weiss. 1980. "The regional diffusion and adoption of the steam engine in American manufacturing." *The Journal of Economic History* 40 (2): 281–308.

Atlas Châtel & Dollfus. 1931. *Les houillères européennes*. Paris: Société de Documentation Industrielle.

Autor, David H, Arindrajit Dube, and Annie McGrew. 2023. "The unexpected compression: Competition at work in the low wage labor market." Working paper 31010, National Bureau of Economic Research.

Autor, David H, Frank Levy, and Richard J Murnane. 2003. "The skill content of recent technological change: An empirical exploration." *The Quarterly Journal of Economics* 118 (4): 1279–1333.

Azar, José, Marina Chugunova, Klaus Keller, and Sampsa Samila. 2023. "Monopsony and Automation." Working paper 23-21, Max Planck Institute for Innovation & Competition.

Bandourian, Raouf, James B. McDonald, and Robert S. Turley. 2003. "A Comparison of Parametric Models of Income Distribution across Countries and over Time." *Estadística* 55: 135–152.

Bessen, James. 2012. "Was mechanization de-skilling? The origins of task-biased technical change." Working paper 11-13, Boston University School of Law.

Blomme, Jan. 1993. "Produktie, produktiefactoren en produktiviteit: De Belgische landbouw 1846–1910." *Revue belge d'histoire contemporaine–Belgisch Tijdschrift voor Nieuwste Geschiedenis* 24 (1-2): 275–293.

Briavoinne, Natalis. 1839. *De l'industrie en Belgique: Causes de décadence et de prospérité*. Brussels: Société Nationale.

Buyst, Erik, and Vincent Delabastita. 2023. "Regional Inequalities in Nineteenth-Century Female Wages: Evidence from Belgium." *The Journal of Interdisciplinary History* 54 (1): 83–110.

Buyst, Erik. Forthcoming. "Changes in the occupational structure of Belgium: New estimates for the 1846–1910 period." In *Occupational structure, industrialization and economic growth in a comparative perspective*, edited by Osamu Saito and Leigh Shaw-Taylor. Cambridge: Cambridge University Press.

Card, David, Ana Rute Cardoso, Joerg Heining, and Patrick Kline. 2018. "Firms and labor market inequality: Evidence and some theory." *Journal of Labor Economics* 36 (S1): S13–S70.

Caselli, Francesco, and Alan Manning. 2019. "Robot arithmetic: New technology and wages." *American Economic Review: Insights* 1 (1): 1–12.

Chlepner, Ben-Serge. 1972. *Cent ans d'histoire sociale en Belgique*. Brussels: Éditions de l'Université de Bruxelles.

Clark, Gregory. 2005. "The condition of the working class in England, 1209–2004." *Journal of Political Economy* 113 (6): 1307–1340.

Clark, Gregory. 2007. *A farewell to alms: A brief economic history of the world*. Princeton: Princeton University Press.

Commons, John Rogers. 1921. *Trade Unionism and Labor Problems*. Boston: Ginn and Co..

Crafts, Nicholas, and Terence C Mills. 2022. "Considering the counterfactual: Real wages in the First Industrial Revolution." *The Economic Journal* 132 (645): 1994–2006.

Dagum, Camilo. 1977. "A new model of personal income distribution: Specification and estimation." *Économie appliquée* 30 (3): 413–437.

De Brabander, Guido L. 1984. *De regionaal-sectoriële verdeling van de economische activiteit in België (1846-1979): Een kritische studie van het bronnenmateriaal*. Bijdragen van het Interuniversitair Centrum voor Hedendaagse Geschiedenis. Brussels: Nauwaerts.

De Herdt, Réné. 1996. "Child labour in Belgium: 1800–1914." In *Child Labour in Historical Perspective 1800-1985: Case Studies from Europe, Japan and Colombia*, edited by Hugh Cunningham and Pier Paolo Viazzo, 23–40. Florence: UNICEF.

De Pleijt, Alexandra, Alessandro Nuvolari, and Jacob Weisdorf. 2020. "Human capital formation during the First Industrial Revolution: Evidence from the use of steam engines." *Journal of the European Economic Association* 18 (2): 829–889.

Degrève, Daniel. 1982. *Le commerce extérieur de la Belgique, 1830-1913-1939: Présentation critique des données statistiques*. vol. 1b. Brussels: Palais des Académies.

Delabastita, Vincent, and Michael Rubens. 2025. "Colluding against workers." *Journal of Political Economy* 133 (6): 1796—-1839.

DiNardo, John, Nicole M Fortin, and Thomas Lemieux. 1996. "Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach." *Econometrica* 64 (5): 1001–1044.

Ducpétiaux, Edouard. 1843. *Le paupérisme en Belgique: causes et remèdes*. Brussels: Meline, Cans et Compagnie.

Dustmann, Christian, Attila Lindner, Uta Schönberg, Matthias Umkehrer, and Philipp vom Berge.

2022. “Reallocation Effects of the Minimum Wage*.” *The Quarterly Journal of Economics* 137 (1): 267–328.

Esposito, Elena, and Scott F Abramson. 2021. “The European coal curse.” *Journal of Economic Growth* 26: 77–112.

Federico, Giovanni, Alessandro Nuvolari, and Michelangelo Vasta. 2023. “Inequality in pre-industrial Europe (1260–1850): New evidence from the labor share.” *Review of Income and Wealth* 69 (2): 347–375.

Feinstein, Charles H. 1988. “The rise and fall of the Williamson curve.” *The Journal of Economic History* 48 (3): 699–729.

Feinstein, Charles H. 1998. “Pessimism perpetuated: Real wages and the standard of living in Britain during and after the Industrial Revolution.” *The Journal of Economic History* 58 (3): 625–658.

Feldman, Naomi E, and Karine van der Beek. 2016. “Skill choice and skill complementarity in eighteenth century England.” *Explorations in Economic History* 59: 94–113.

Fiszbein, Martin, Jeanne Lafortune, Ethan G. Lewis, and José Tessada. 2024. “Powering Up Productivity: The Effects of Electrification on U.S. Manufacturing.”

Franck, Raphaël, and Oded Galor. 2022. “Technology-Skill Complementarity in Early Phases of Industrialisation.” *The Economic Journal* 132 (642): 618–643.

Gallardo-Albarrán, Daniel, and Herman De Jong. 2021. “Optimism or pessimism? A composite view on English living standards during the Industrial Revolution.” *European Review of Economic History* 25 (1): 1–19.

Goossens, Martine. 1993. *The economic development of Belgian agriculture : A regional perspective 1812-1846*. Leuven: Leuven University Press.

Van der Hallen, Peter. 2011. “Industrial Dynamics in the Food Industry in Belgium, 1890-1940.” PhD dissertation, KU Leuven. Leuven.

Henderson, Louis. 2024. “The expansion of basic education during ‘deskilling’ technological change in England and Wales, c. 1780–1830.” *The Economic History Review*.

Hlasny, Vladimir. 2021. “Parametric representation of the top of income distributions: Options, historical evidence, and model selection.” *Journal of Economic Surveys* 35 (4): 1217–1256.

Hoes, Olivier AC, Lourens JJ Meijer, Ruud J Van Der Ent, and Nick C Van De Giesen. 2017. “Systematic high-resolution assessment of global hydropower potential.” *PloS one* 12 (2): e0171844.

Hornbeck, Richard, Shanon Hsuan-Ming Hsu, Anders Humlum, and Martin Rotemberg. 2023. “Technological Stickiness: Switching and Entry in the Long Transition from Water to Steam Power.” working paper, University of Chicago.

Huberman, Michael, and Wayne Lewchuk. 2003. “European economic integration and the labour compact, 1850–1913.” *European Review of Economic History* 7 (1): 3–41.

Huberman, Michael, Christopher M Meissner, and Kim Oosterlinck. 2017. “Technology and geography in the Second Industrial Revolution: New evidence from the margins of trade.” *The Journal of Economic History* 77 (1): 39–89.

Humphries, Jane, and Carmen Sarasúa. 2012. “Off the record: Reconstructing women’s labor force participation in the European past.” *Feminist Economics* 18 (4): 39–67.

Humphries, Jane, and Jacob Weisdorf. 2019. "Unreal wages? Real income and economic growth in England, 1260–1850." *The Economic Journal* 129 (623): 2867–2887.

Jacquemyns, Guillaume. 1929. *Histoire de la crise économique des Flandres (1845-1850)*. Brussels: M. Lamertin.

Juhasz, Reka, Mara Squicciarini, and Nico Voigtlaender. 2024. "Technology Adoption and Productivity Growth: Evidence from Industrialization in France." *Journal of Political Economy*. Publisher: The University of Chicago Press.

Katz, Lawrence F, and Robert A Margo. 2014. "Technical change and the relative demand for skilled labor: The United States in historical perspective." In *Human Capital in History: The American Record*, edited by Leah Platt Boustan, Carola Frydman, and Robert A Margo, 15–57: University of Chicago Press.

Kleiber, Christian. 2008. "A Guide to the Dagum Distributions." In *Modeling Income Distributions and Lorenz Curves*, edited by Duangkamon Chotikapanich, 97–117. New York: Springer New York.

Lafortune, Jeanne, Ethan Lewis, and José Tessada. 2019. "People and machines: A look at the evolving relationship between capital and skill in manufacturing, 1860–1930, using immigration shocks." *The Review of Economics and Statistics* 101 (1): 30–43.

Langella, Monica, and Alan Manning. 2021. "The Measure of Monopsony." *Journal of the European Economic Association* 19 (6): 2929–2957.

Lebrun, Pierre, Marinette Bruwier, Jan Dhont, and Georges Hansotte. 1981. *Essai sur la révolution industrielle en Belgique: 1770-1847*. Histoire quantitative et développement de la Belgique. Brussels: Palais des Académies.

Lesthaeghe, Ron J. 1977. *The decline of Belgian fertility, 1800-1970*. Princeton: Princeton University Press.

Lindert, Peter H, and Jeffrey G Williamson. 1983. "English workers' living standards during the Industrial Revolution: A new look." *The Economic History Review* 36 (1): 1–25.

Luyten, Dirk. 1995. *Sociaal-economisch overleg in België sedert 1918*. Brussels: VUpress.

Manning, Alan. 2021. "Monopsony in Labor Markets: A Review." *ILR Review* 74 (1): 3–26.

Mareska, Daniel Joseph Benoit, and J Heyman. 1845. *Enquête sur le travail et la condition physique et morale des ouvriers employés dans les manufactures de coton, à Gand*. Ghent: Imprimerie de F. et E. Gyselynck.

Martí-Henneberg, Jordi. 2013. "European integration and national models for railway networks (1840–2010)." *Journal of Transport Geography* 26: 126–138.

McDonald, James B. 1984. "Some Generalized Functions for the Size Distribution of Income." *Econometrica* 52 (3): 647–665.

McDonald, James B., and Michael Ransom. 2008. "The Generalized Beta Distribution as a Model for the Distribution of Income: Estimation of Related Measures of Inequality." In *Modeling Income Distributions and Lorenz Curves*, edited by Duangkamon Chotikapanich, 147–166. New York: Springer New York.

Mokyr, Joel. 1976. *Industrialization in the Low Countries, 1795-1850*. London: Yale University Press.

Mokyr, Joel. 1990. *The lever of riches: Technological creativity and economic progress*. New York: Oxford University Press.

Mokyr, Joel. 2002. *The Gifts of Athena: Historical Origins of the Knowledge Economy*. Princeton: Princeton University Press.

Mokyr, Joel, and Hans-Joachim Voth. 2010. "Understanding growth in Europe, 1700-1870: Theory and evidence." In *The Cambridge economic history of modern Europe,* edited by Stephen Broadberry and Kevin O'Rourke, vol. 1, 7–42. Cambridge: Cambridge University Press.

Muendler, Marc-Andreas. 2009. "Converter from SITC to ISIC." working paper, University of California-San Diego.

Musson, Albert E. 1976. "Industrial motive power in the United Kingdom, 1800-70." *The Economic History Review* 29 (3): 415–439.

Office du Travail. 1896. "Recensement général des industries & des métiers (31 octobre 1896): Volume XVIII: Exposé Général des méthodes et des résultats."

O'Brien, Patrick. 1983. "Transport and Economic Development in Europe, 1789–1914." In *Railways and the Economic Development of Western Europe, 1830–1914,* edited by Patrick O'Brien. London: Palgrave Macmillan.

Reichardt, Hugo. 2025. "Scale-biased technical change and inequality." working paper, Centre de Recerca en Economica Internacional (CREI).

Ridolfi, Leonardo, Carla Salvo, and Jacob Weisdorf. 2023. "The Effect of Mechanisation on Labour: Evidence from the Diffusion of Steam." working paper, Competitive Advantage in the Global Economy (CAGE).

Rubens, Michael. 2024. "Labor market power and factor-biased technology adoption." working paper, UCLA.

Scholliers, Peter. 1991. "Industrial wage differentials in nineteenth-century Belgium." In *Income Distribution in Historical Perspective,* edited by Yehojachin Simon Brenner, Hartmut Kaelble, and Mark Thomas, 96–116. Cambridge: Cambridge University Press.

Scholliers, Peter. 1995. "A century of real industrial wages in Belgium, 1840–1939." In *Labour's Reward: Real Wages and Economic Change in 19th- and 20th-century Europe,* edited by Peter Scholliers and Vera Zamagni, 106–137. Aldershot: Edward Elgar Publishing.

Segers, Yves. 2003. *Economische groei en levensstandaard: Particuliere consumptie en voedselverbruik in België, 1800-1913*. Leuven: Leuven University Press.

Singh, S. K., and G. S. Maddala. 1976. "A Function for the Size Distribution of Incomes." *Econometrica* 44 (5): 963–970.

Slichter, Sumner. 1931. *Modern Economic Society*. 2nd ed. New York: Henry Holt.

Statistique de la Belgique. 1846. "Industrie. Recensement général. 15 octobre 1846.."

Van den Eeckhout, Patricia. 2005. "Van werkboekje tot arbeidscontract. De negentiende-eeuwse arbeidsrelaties revisited." *Belgisch Tijdschrift voor Nieuwste Geschiedenis* 35 (2-3): 153–200.

Van Neck, Anne. 1979. *Les débuts de la machine à vapeur dans l'industrie Belge, 1800-1850*. Histoire Quantitative et Développement de la Belgique. Brussels: Palais des Académies.

Von Hippel, Paul T, Samuel V Scarpino, and Igor Holas. 2016. "Robust estimation of inequality from binned incomes." *Sociological Methodology* 46 (1): 212–251.

Voth, Hans-Joachim, Bruno Caprettini, and Alex Trew. 2024. "Fighting for Growth: Labor scarcity and technological progress during the British industrial revolution." *Working Papers*. Number: 2022_15 Publisher: Business School - Economics, University of Glasgow.

Webb, Sidney, and Beatrice Webb. 1897. *Industrial Democracy: Volume Two*. London: Longmans Green.
Van der Wee, Herman. 1996. "The Industrial Revolution in Belgium." In *The Industrial Revolution in national context: Europe and the USA,* edited by Mikuláš Teich and Roy Porter, 64–77. Cambridge: Cambridge University Press.
Williamson, Jeffrey G. 1985. *Did British capitalism breed inequality?*. Boston: Allen and Unwin.
van Zanden, Jan Luiten. 2009. "The skill premium and the 'Great Divergence'." *European Review of Economic History* 13 (1): 121–153.

Appendices - for online publication only

Appendix A. A model

A.1. Equilibrium expressions

From the firm's maximization problem, we derived Equation (11):

$$\ln(w_j) = \ln\left(\psi_j \frac{\epsilon - (1+\epsilon)\epsilon_{\theta w}}{(1+\epsilon)(1-\epsilon_{\theta w})}\right) - \ln(l_j) \tag{A1}$$

and we want to solve for $\ln(w_j)$ by substituting out $\ln(l_j)$ to get Equation (12).

To get an expression for $\ln(l_j)$, first substitute Equation (2) into (4) to get:

$$\ln(a_j) = \epsilon(1-\epsilon_{\theta w})\ln(w_j) + \ln(\lambda L) \tag{A2}$$

Next substitute this expression into $\ln(l_j = \ln(a_j) - \epsilon_{\theta w}\ln(w_j)$:

$$\begin{aligned} \ln(l_j) &= \epsilon(1-\epsilon_{\theta w})\ln(w_j) + \ln(\lambda L) - \epsilon_{\theta w}\ln(w_j) \\ \ln(l_j) &= [\epsilon(1-\epsilon_{\theta w}) - \epsilon_{\theta w}]\ln(w_j) + \ln(\lambda L) \end{aligned} \tag{A3}$$

which is Equation (5). Substitute Equation (5) into (11):

$$\begin{aligned} \ln(w_j) &= \ln\left(\psi_j \frac{\epsilon - (1+\epsilon)\epsilon_{\theta w}}{(1+\epsilon)(1-\epsilon_{\theta w})}\right) - \ln(l_j) \\ \ln(w_j) &= \ln\left(\psi_j \frac{\epsilon - (1+\epsilon)\epsilon_{\theta w}}{(1+\epsilon)(1-\epsilon_{\theta w})}\right) - [\epsilon(1-\epsilon_{\theta w}) - \epsilon_{\theta w}]\ln(w_j) - \ln(\lambda L) \end{aligned} \tag{A4}$$

Rearranging terms gives Equation (12):

$$\ln(w_j) = \underbrace{\frac{1}{(1+\epsilon)(1-\epsilon_{\theta w})}\ln\left(\psi_j \frac{\epsilon - (1+\epsilon)\epsilon_{\theta w}}{(1+\epsilon)(1-\epsilon_{\theta w})}\right)}_{\equiv A} - \frac{1}{(1+\epsilon)(1-\epsilon_{\theta w})}\ln(\lambda L) \tag{A5}$$

Finally, substituting Equation (12) into (11) gives Equation (13):

$$\begin{aligned} \ln(l_j) &= \ln\left(\psi_j \frac{\epsilon - (1+\epsilon)\epsilon_{\theta w}}{(1+\epsilon)(1-\epsilon_{\theta w})}\right) - \ln(w_j) \\ \ln(l_j) &= \underbrace{\frac{\epsilon - (1+\epsilon)\epsilon_{\theta w}}{(1+\epsilon)(1-\epsilon_{\theta w})}\ln\left(\psi_j \frac{\epsilon - (1+\epsilon)\epsilon_{\theta w}}{(1+\epsilon)(1-\epsilon_{\theta w})}\right)}_{\equiv B} + \frac{1}{(1+\epsilon)(1-\epsilon_{\theta w})}\ln(\lambda L) \end{aligned} \tag{A6}$$

A.2. Comparative statics

Deriving term A in Equation (12) w.r.t. a *decrease in* $\epsilon_{\theta w}$ gives:

$$-\frac{\partial A}{\partial \epsilon_{\theta w}} = \frac{1}{(1+\epsilon)(1-\epsilon_{\theta w})^2}\left[\frac{1}{\epsilon-(1+\epsilon)\epsilon_{\theta w}} - \ln\left(\psi_j \frac{\epsilon-(1+\epsilon)\epsilon_{\theta w}}{(1+\epsilon)(1-\epsilon_{\theta w})}\right)\right] \tag{A7}$$

which is decreasing in ψ_j such that wage growth is higher in low-wage firms.

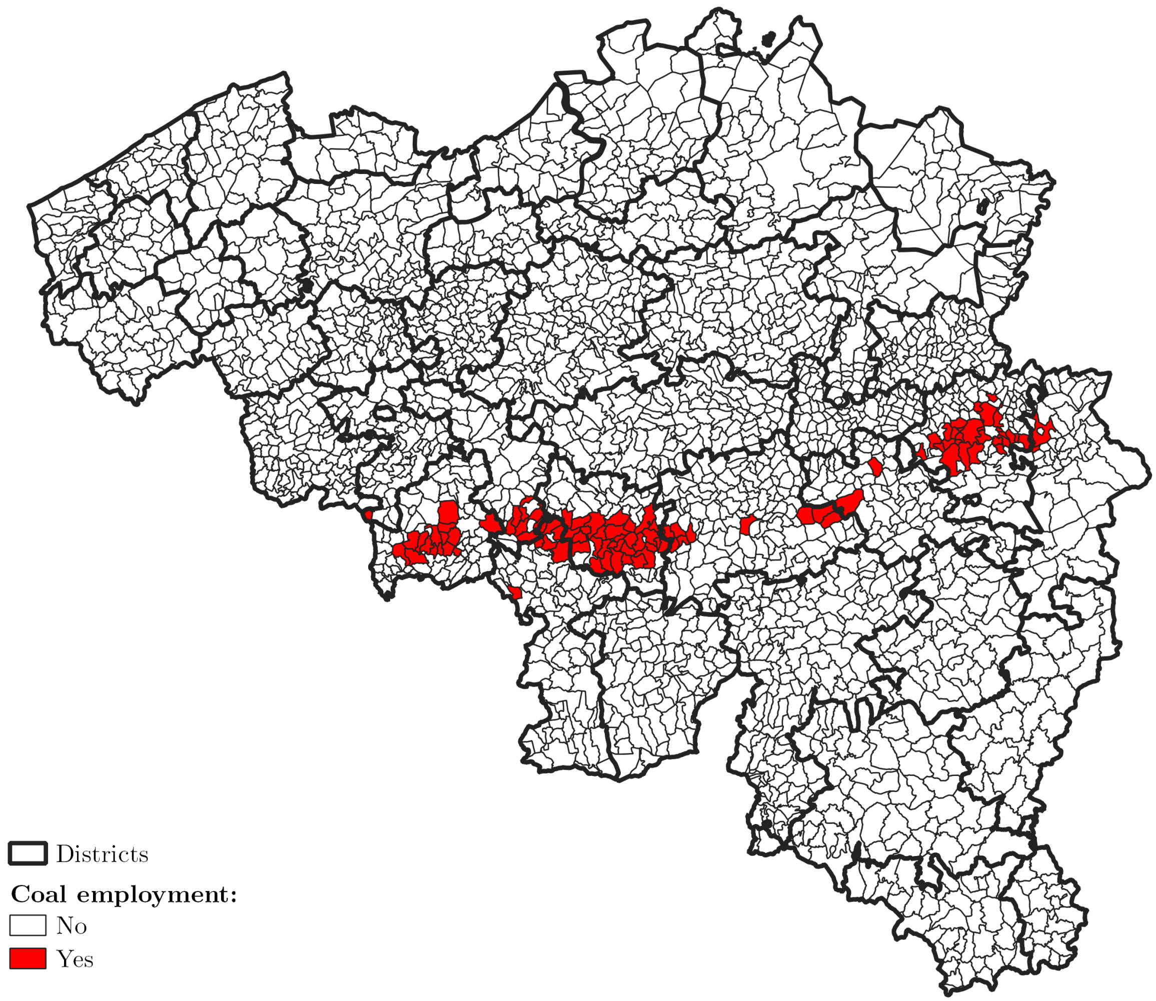
Deriving term B in Equation (13) w.r.t. a decrease in $\epsilon_{\theta w}$ gives:

$$-\frac{\partial B}{\partial \epsilon_{\theta w}} = \frac{1}{(1+\epsilon)(1-\epsilon_{\theta w})^2}\left[1+\ln\left(\psi_j \frac{\epsilon-(1+\epsilon)\epsilon_{\theta w}}{(1+\epsilon)(1-\epsilon_{\theta w})}\right)\right] \tag{A8}$$

which is increasing in ψ_j such that workers relocate from low-wage to high-wage firms.

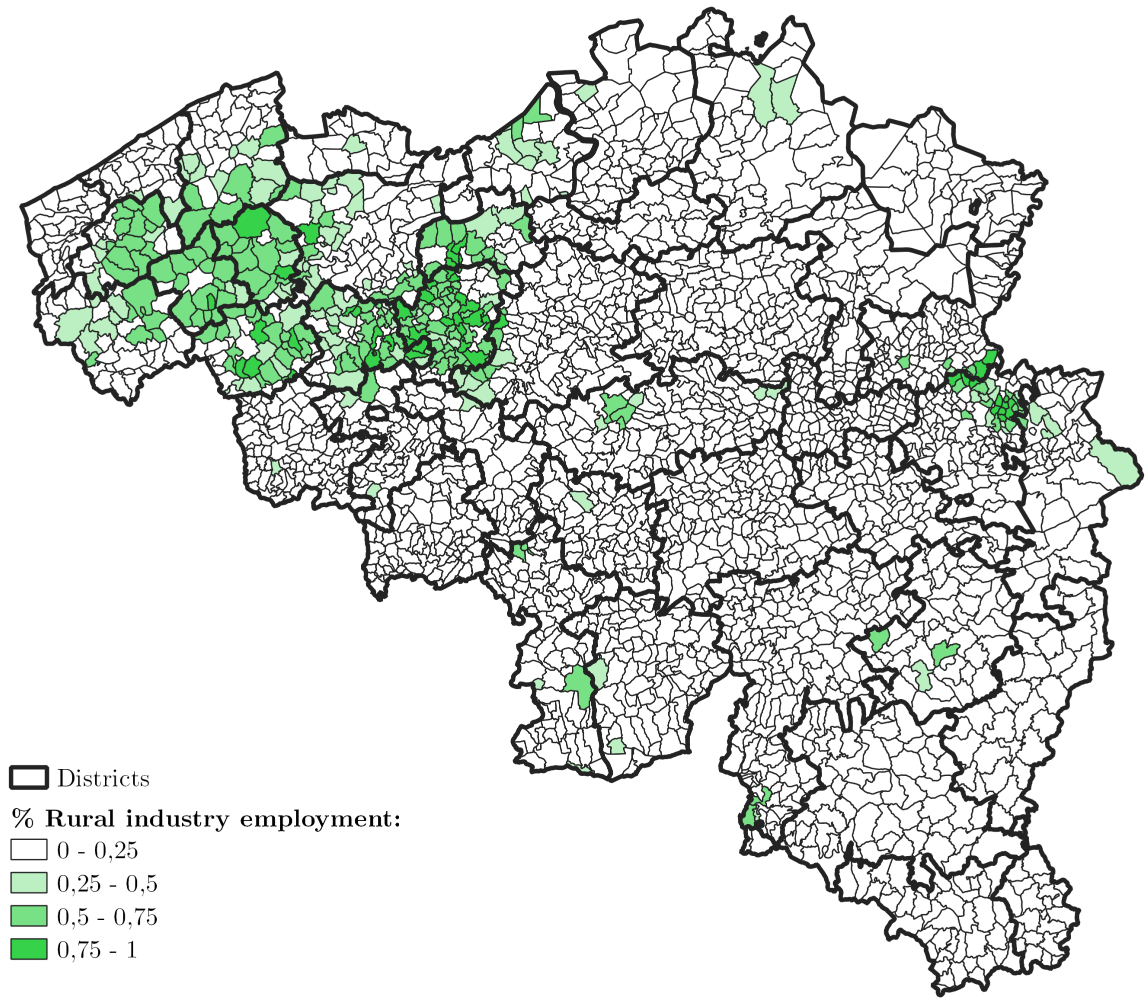
Appendix B. Historical context

FIGURE B1. Presence of coal mine employment in Belgium, community level, 1896



Source: Industrial Census of 1896

FIGURE B2. Share of industrial employment in rural industries in Belgium, community level, 1896



Source: Industrial Census of 1896

Appendix C. Data

C.1. The coverage of employment in the industrial census of 1896

As illustrated in Table C1, the organizers of the IC1896 differentiated between employment and wage counts. The former allow us to investigate the coverage of the employment figures, as taken from the wage books. In Figure C1, we compare aggregated employment figures from volumes I and II (both *manual employment* and *total employment*), and from volumes IX to XIV (employment from aggregating all wage earner counts). This comparison reveals that the latter are a satisfactory approximation of total manual employment, as a large majority of manual workers are included in the wage sample.

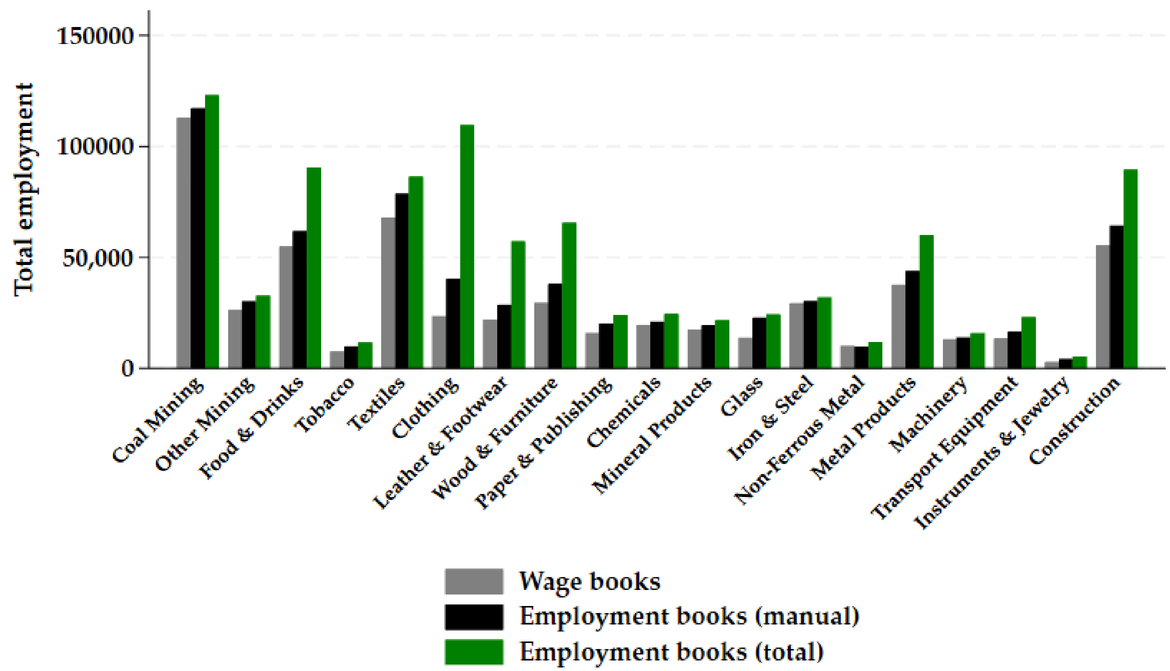
Our wage sample does, however, appear to underestimate total employment, which includes non-manual employment. This problem is confined to a selection of sectors, with clothing and other handcraft industries being the most underrepresented in the wage sample. The reason for this can be found in the exclusion of domestic industries, which were especially prominent in these types of economic activity: domestic, and typically female, workers were characterized as non-manual workers in the IC1896. Given that this paper is exclusively aimed at factory-based production, this undersampling is of little concern. Furthermore, the IC1846 also omitted domestic labor, making this restriction to factory labor necessary.

Table C1. Coverage of the respective variables in the industrial censuses of 1846 and 1896

Source		**Employment**	**Horsepower**	**Wages**
IC1846		District/urban	District/urban	District/urban
				9 wage categories
IC1896	vol. I-II	Community	Community	✖
	vol. IX-XIV	District/urban (size)	✖	District/urban (size)
				Firm & occupation
				13 wage categories

Notes: 'District/urban' means that the variable is available at the district (*arrondissement*) level, with a distinction being made for urban and rural observations. 'District/urban (size)' observations allow us to differentiate between communities of seven different demographic sizes. The wage data of IC1896 are also available at the occupation and firm level, albeit anonymized.

FIGURE C1. Employment per sector in 1896 according to different volumes



Notes: Employment from the *wage* books is based on volumes IX to XIV of the IC1896. Employment figures from the *manual employment* and *total employment* books are both adapted from volumes I and II of the same census.

Source: Authors' database (see text). Volumes I and II were digitized by the Quetelet Center for Quantitative Historical Research of Ghent University.

C.2. Comparing the Industrial Censuses (IC) of 1846 and 1896

Aside from the requirement to be exclusively aimed at the consumer market, the object of the 1896 census was fairly similar to the one in 1846. As a consequence, both surveys are regarded to be reasonably comparable (De Brabander 1984, 75; Scholliers 1991). However, some challenges limiting the comparability between both surveys had to be addressed.

First, the IC's sectoral classification system changes fundamentally throughout different iterations of the census. To alleviate this, we linked the 1846 and 1896 industry classifications to their corresponding four-digits codes (*groups*) in the *International Standard Industrial Classification of All Economic Activities* (ISIC revision 2). These ISIC codes were then used to aggregate the respective industries into 19 consistent groups, as displayed in Table C2.

TABLE C2. Industries and their respective ISIC Rev.2 major groups

Nr.	Industry	ISIC Rev.2 Major group
1	Coal Mining	210
2	Other Mining	230, 290
3	Food & Drinks	311-313
4	Tobacco	314
5	Textiles	321
6	Clothing	322
7	Leather & Footwear	323, 324
8	Wood & Furniture	331, 332
9	Paper & Publishing	341, 342
10	Chemicals	220, 351-356
11	Mineral Products	361, 369
12	Glass	362
13	Iron & Steel	371
14	Non-Ferrous Metal	372
15	Metal Products	381
16	Machinery	382, 383
17	Transport Equipment	384
18	Instruments & Jewelry	385, 390
19	Construction	500

Second, both surveys present the wage data in grouped form, albeit in a changing number of wage categories (9 in 1846, 13 in 1896). As explained in the main text, we fit these categorical wage data to obtain a continuous measure of inequality. To further facilitate comparison between both sources, we use Segers's CPI (2003, 622) to calculate wages into 1910 Belgian Francs (BEF).

A final caveat relates to the changing nature of daily wages. In contrast to the 1896 IC, the 1846 survey does not present us with working time, but calculates daily wages based on a theoretical working day of about 10 to 12 hours. Given that average working days were presumably longer, daily wages are likely to have been underestimated (Statistique de la Belgique 1846, XIX). However, we do not think that this drives the observed compression in lower-tail wage inequality because we expect that, if anything, the underestimation of working hours in 1846 is more severe for low-wage workers.

C.3. Agricultural employment

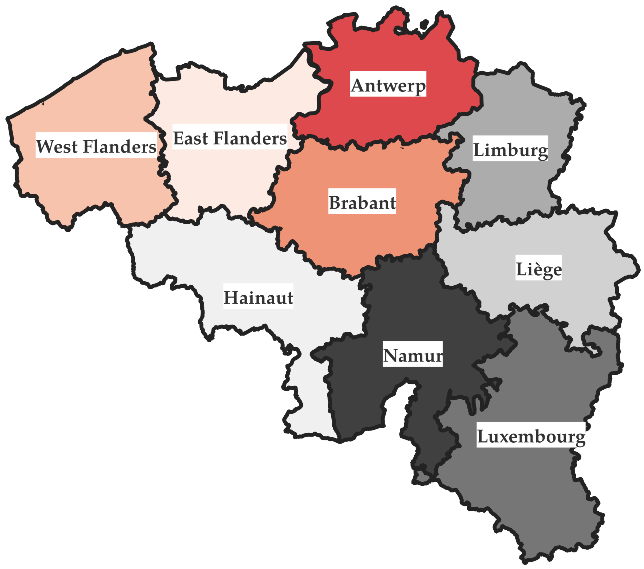
We obtain agricultural employment at district level in 1846 and 1896 from community-level employment counts in the agricultural censuses (AC) of 1846 and 1895 respectively.[38] The AC of 1895 presents a comprehensive data variable on the entire agricultural population. For 1846, the AC distinguishes between agricultural staff, family members and the numbers of days work performed by casual labor. We follow Goossens (1993, 238-239) in defining agricultural employment as the sum of the former two categories, agricultural workers and their family. Casual labor was not included as most Belgian casual laborers were either owners of a small plot of land themselves or already included in the category of family members. The census takers were supposed to double count these workers in the category of casual labor.

[38]These data at the community level have been digitized by the Quetelet Center for Quantitative Historical Research of Ghent University, and we thank them for access to this source.

C.4. Provinces and districts in 19th-century Belgium

FIGURE C2. Belgium with 1890 borders

A. Provinces



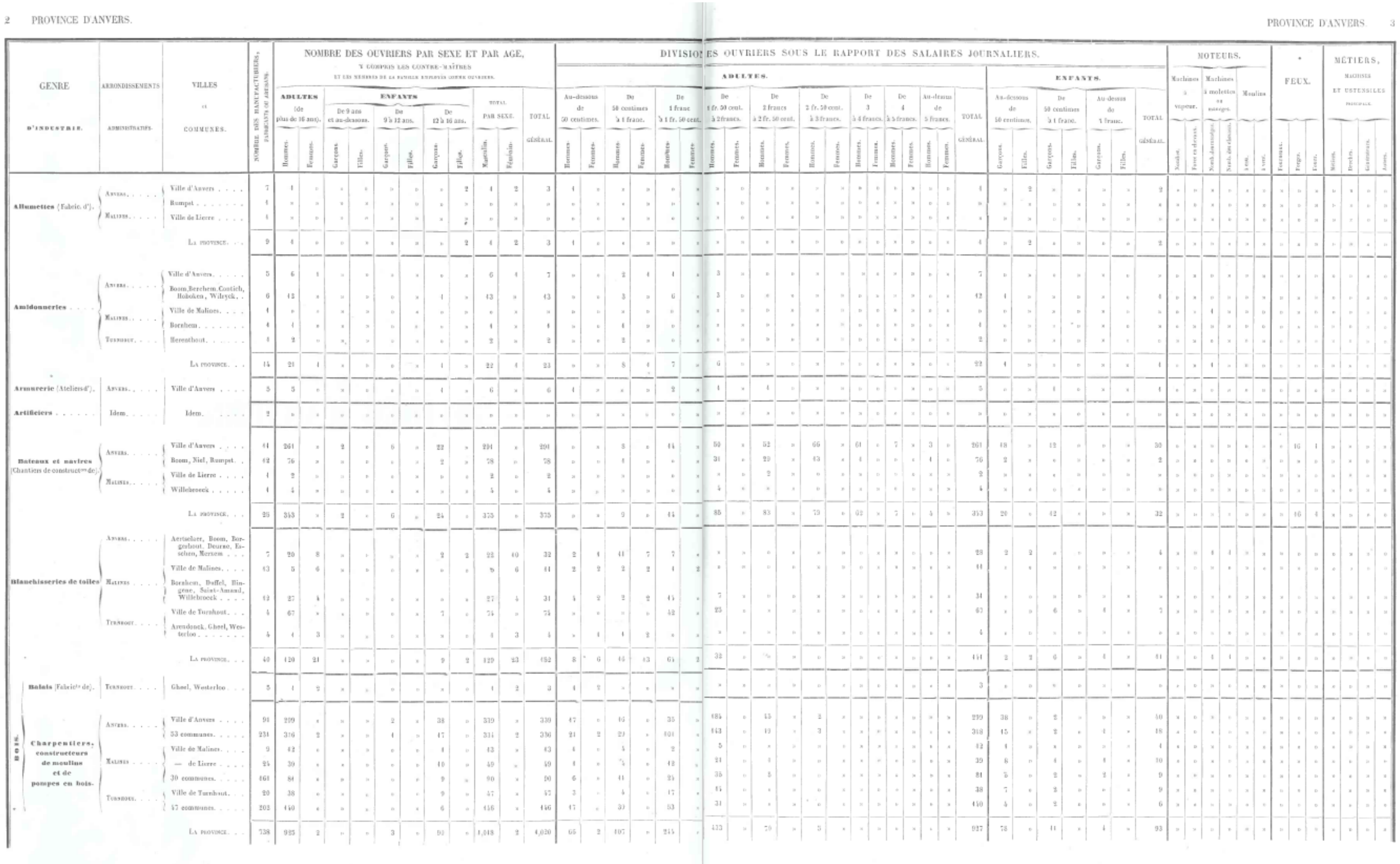
B. Districts

Sources: Authors' rendition. We thank Quetelet Center for Quantitative Historical Research of Ghent University for access to their GIS files.

Appendix D. Wages

D.1. Data sheets in the Industrial Censuses

FIGURE D3. Wages and employment in the Industrial Census of 1846



2 PROVINCE D'ANVERS. — PROVINCE D'ANVERS. 3

GENRE D'INDUSTRIE. — ARRONDISSEMENTS ADMINISTRATIFS. — VILLES ET COMMUNES. — NOMBRE DES MANUFACTURES, FABRIQUES OU ATELIERS. — NOMBRE DES OUVRIERS PAR SEXE ET PAR AGE, Y COMPRIS LES CONTRE-MAÎTRES. — DIVISION DES OUVRIERS SOUS LE RAPPORT DES SALAIRES JOURNALIERS. — MOTEURS. — FEUX. — MÉTIERS, MACHINES ET USTENSILES.

Allumettes (Fabric. d'). — Amidonneries. — Armurerie (Ateliers d'). — Artificiers. — Bateaux et navires (Chantiers de construct.ion de). — Blanchisseries de toiles. — Balais (Fabric.es de). — BOIS. Charpentiers, constructeurs de moulins et de pompes en bois.

Sources: Statistique de la Belgique (1846), pages 2-3

FIGURE D4. Wages and employment in the Industrial Census of 1896

CADRE XI. — 2 — — 3 — **CADRE XI.**

N. B. — Dans ce cadre, on a présenté comme entreprises distinctes les divisions industrielles des entreprises qui en comprennent plusieurs.

ENTREPRISES ET DIVISIONS D'ENTREPRISES EN ACTIVITÉ OCCUPANT DES OUVRIERS ÉTRANGERS A LA FAMILLE DES EXPLOITANTS.

Répartition du personnel ouvrier d'après le taux des salaires.

N. B. — Les taux des salaires ont été établis d'après les livres de paie des chefs d'entreprise, pour la dernière paie qui a précédé le recensement; ils représentent non des moyennes, mais le revenu réel d'une journée normale de travail pour chaque ouvrier et ouvrière à la fin du mois d'octobre 1896.

N. B. — Dans ce cadre, on a présenté comme entreprises distinctes les divisions industrielles des entreprises qui en comprennent plusieurs.

INDUSTRIES TEXTILES. — Fabrication des fils et des tissus de chanvre et de jute.

Numéro d'ordre. (1)	EXPLOITATIONS INDUSTRIELLES ET MÉTIERS. (2)	SITUATION DES ENTREPRISES ET DIVISIONS D'ENTREPRISES. (3)	NOMBRE CONSIDÉRÉ D'ENTREPRISES EN ACTIVITÉ. (4)	PERSONNEL OUVRIER DES ENTREPRISES CONSIDÉRÉES. (5)	NATURE DU TRAVAIL EFFECTUÉ. (6)	CATÉGORIES D'OUVRIERS par spécialités de travail [non compris les contremaîtres, porions, surveillants, etc.]. (7)	MODE DE RÉMUNÉRATION T : au temps. [hre : heure; — jée : journée, — sem. : semaine, — qne : quinzaine]. — P : à la pièce, à la quantité. [ind. : individuellement, — coll. : collectivement.] (8)
4450	**Chanvre** (*filatures mécaniques de*).	ARRONDISSEMENT DE St-NICOLAS. 1 petite ville.	1	127	FABRICATION.	Dévideuses	P.—ind.
						Fileuses	T.—hre.
						id. (aides)	T.—hre.
						Ouvrières de préparation	T.—hre.
						Peigneurs à la main	P.—ind.
						id. à la machine	T.—hre.
					SERVICES GÉNÉRAUX.	Charpentier	T.—hre.
						Chauffeur	T.—hre.
						Machiniste	T.—hre.
						Mécanicien	T.—hre.
4451	**Chanvre** (*filatures mécaniques de*).	ARRONDISSEMENT DE St-NICOLAS. 1 petite ville.	1	5	FABRICATION.	Fileurs	T.—jée.
						Retordeurs	T.—jée.
4452	**Chanvre** (*filatures mécaniques de*).	ARRONDISSEMENT DE TERMONDE. 1 grosse commune.	1	13	FABRICATION.	Bobineurs	P.—ind.
						Fileurs	P.—ind.
4453	**Chanvre** (*filatures mécaniques de*).	ARRONDISSEMENT DE TERMONDE. 1 grosse commune.	2	11	FABRICATION.	Fileurs	T.—jée.
						Séranceurs	T.—jée.
	Chanvre (*filatures mécaniques de*).	LE ROYAUME.	5	156	TOTAUX GÉNÉRAUX.		—
4454	**Chanvre** (*peignages mécaniques de*).	ARRONDISSEMENT DE St-NICOLAS. 1 petite ville.	1	20	FABRICATION.	Dévideurs	P.—ind.
						id.	T.—hre.
	Chanvre (*peignages mécaniques de*).	LE ROYAUME.	1	20	TOTAUX GÉNÉRAUX.		—
4455	**Jute, jute et chanvre, jute et étoupe** (*filatures mécaniques de*).	ARRONDISSEMENT DE ROULERS. 1 ville.	1	77	FABRICATION.	Cardeurs	T.—jée.
						Fileuses, dévideuses et épouleuses.	T.—jée.
						Fileuses (aides)	—
						Séparateurs de jute	—
					SERVICES GÉNÉRAUX.	Forgerons et graisseurs	—
						Magasiniers	—
4456	**Jute, jute et chanvre, jute et étoupe** (*filatures mécaniques de*).	ARRONDISSEMENT D'ALOST. 1 ville.	1	26	FABRICATION.	Cardeurs	T.—jée.
						Fileuses	T.—jée.
						id. (apprenties)	T.—jée.

NOMBRE D'OUVRIERS ET D'OUVRIÈRES DE MOINS DE 16 ANS

No.	Catégorie (7)	Garçons: Nombre d'heures de travail par jour [repos déduits] (9)	Garçons: TOTAL (10)	Garçons, ayant gagné par jour: moins de 0.50 fr. (11)	de 0.50 à 0.99 fr. (12)	de 1.00 à 1.49 fr. (13)	1.50 fr. et plus. (14)	Filles: Nombre d'heures de travail par jour [repos déduits] (15)	Filles: TOTAL (16)	Filles, ayant gagné par jour: moins de 0.50 fr. (17)	de 0.50 à 0.99 fr. (18)	1.00 fr. et plus. (19)
4450	Dévideuses	—	—	—	—	—	—	11	2	—	—	2
	Fileuses	—	—	—	—	—	—	—	—	—	—	—
	id. (aides)	—	—	—	—	—	—	11	12	—	12	—
	Ouvrières de préparation	—	—	—	—	—	—	11	5	—	5	—
	Peigneurs à la main	—	—	—	—	—	—	—	—	—	—	—
	id. à la machine	11	7	—	7	—	—	—	—	—	—	—
	Charpentier	—	—	—	—	—	—	—	—	—	—	—
	Chauffeur	—	—	—	—	—	—	—	—	—	—	—
	Machiniste	—	—	—	—	—	—	—	—	—	—	—
	Mécanicien	—	—	—	—	—	—	—	—	—	—	—
4451	Fileurs	11½	2	—	—	2	—	—	—	—	—	—
	Retordeurs	—	—	—	—	—	—	—	—	—	—	—
4452	Bobineurs	12	1	—	1	—	—	—	—	—	—	—
	Fileurs	—	—	—	—	—	—	—	—	—	—	—
4453	Fileurs	—	—	—	—	—	—	11½	3	—	—	3
	Séranceurs	—	—	—	—	—	—	—	—	—	—	—
	TOTAUX GÉNÉRAUX (Chanvre, filatures)	—	10	—	8	2	—	—	22	—	17	5
4454	Dévideurs	—	—	—	—	—	—	—	—	—	—	—
	id.	11	4	—	—	4	—	—	—	—	—	—
	TOTAUX GÉNÉRAUX (Chanvre, peignages)	—	4	—	—	4	—	—	—	—	—	—
4455	Cardeurs	11½	7	—	—	7	—	—	—	—	—	—
	Fileuses, dévideuses et épouleuses	—	—	—	—	—	—	—	—	—	—	—
	Fileuses (aides)	—	—	—	—	—	—	11½	20	—	—	20
	Séparateurs de jute	11½	4	—	—	—	4	—	—	—	—	—
	Forgerons et graisseurs	—	—	—	—	—	—	—	—	—	—	—
	Magasiniers	—	—	—	—	—	—	—	—	—	—	—
4456	Cardeurs	—	—	—	—	—	—	—	—	—	—	—
	Fileuses	—	—	—	—	—	—	—	—	—	—	—
	id. (apprenties)	—	—	—	—	—	—	11	7	7	—	—

NOMBRE D'OUVRIERS ET D'OUVRIÈRES DE PLUS DE 16 ANS — Hommes

No.	Catégorie (7)	Nombre d'heures de travail par jour [repos déduits] (20)	TOTAL (21)	ayant gagné par jour: moins de 1.50 fr. (22)	de 1.50 à 1.99 fr. (23)	de 2.00 à 2.49 fr. (24)	de 2.50 à 2.99 fr. (25)	de 3.00 à 3.49 fr. (26)	de 3.50 à 3.99 fr. (27)	de 4.00 à 4.49 fr. (28)	de 4.50 à 4.99 fr. (29)	de 5.00 à 5.49 fr. (30)	de 5.50 à 5.99 fr. (31)	de 6.00 à 6.49 fr. (32)	de 6.50 à 6.99 fr. (33)	7.00 fr. et plus. (34)
4450	Dévideuses	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	Fileuses	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	id. (aides)	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	Ouvrières de préparation	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	Peigneurs à la main	11	12	—	—	—	12	—	—	—	—	—	—	—	—	—
	id. à la machine	11	23	23	—	—	—	—	—	—	—	—	—	—	—	—
	Charpentier	11	1	—	—	—	1	—	—	—	—	—	—	—	—	—
	Chauffeur	11	1	—	—	1	—	—	—	—	—	—	—	—	—	—
	Machiniste	11	1	—	—	—	1	—	—	—	—	—	—	—	—	—
	Mécanicien	11	1	—	—	—	—	—	1	—	—	—	—	—	—	—
4451	Fileurs	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	Retordeurs	11½	3	—	—	—	3	—	—	—	—	—	—	—	—	—
4452	Bobineurs	12	4	—	2	1	1	—	—	—	—	—	—	—	—	—
	Fileurs	12	6	—	2	2	2	—	—	—	—	—	—	—	—	—
4453	Fileurs	12	3	—	—	3	—	—	—	—	—	—	—	—	—	—
	Séranceurs	11½	2	—	—	2	—	—	—	—	—	—	—	—	—	—
	TOTAUX GÉNÉRAUX (Chanvre, filatures)	—	57	23	4	9	20	—	1	—	—	—	—	—	—	—
4454	Dévideurs	11½	16	—	—	16	—	—	—	—	—	—	—	—	—	—
	id.	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	TOTAUX GÉNÉRAUX (Chanvre, peignages)	—	16	—	—	16	—	—	—	—	—	—	—	—		—
4455	Cardeurs	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	Fileuses, dévideuses et épouleuses	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	Fileuses (aides)	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	Séparateurs de jute	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	Forgerons et graisseurs	11½	8	—	—	—	—	—	8	—	—	—	—	—	—	—
	Magasiniers	11½	3	—	—	3	—	—	—	—	—	—	—	—	—	—
4456	Cardeurs	11	9	—	9	—	—	—	—	—	—	—	—	—	—	—
	Fileuses	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	id. (apprenties)	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—

NOMBRE D'OUVRIERS ET D'OUVRIÈRES DE PLUS DE 16 ANS — Femmes; NOMBRE D'OUVRIERS ET D'OUVRIÈRES DE MOINS ET DE PLUS DE 16 ANS ayant gagné par jour une somme dont le montant n'a pu être déterminé

No.	Catégorie (7)	Nombre d'heures de travail par jour [repos déduits] (35)	TOTAL (36)	ayant gagné par jour: moins de 1.00 fr. (37)	de 1.00 à 1.49 fr. (38)	de 1.50 à 1.99 fr. (39)	de 2.00 à 2.49 fr. (40)	de 2.50 à 2.99 fr. (41)	de 3.00 à 3.49 fr. (42)	de 3.50 à 3.99 fr. (43)	4.00 fr. et plus. (44)	Garçons (45)	Filles (46)	Hommes (47)	Femmes (48)	TOTAL (49)
4450	Dévideuses	11	15	—	15	—	—	—	—	—	—	—	—	—	—	—
	Fileuses	11	27	—	27	—	—	—	—	—	—	—	—	—	—	—
	id. (aides)	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	Ouvrières de préparation	11	20	—	20	—	—	—	—	—	—	—	—	—	—	—
	Peigneurs à la main	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	id. à la machine	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	Charpentier	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	Chauffeur	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	Machiniste	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	Mécanicien	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
4451	Fileurs	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	Retordeurs	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
4452	Bobineurs	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	Fileurs	12	2	—	—	1	1	—	—	—	—	—	—	—	—	—
4453	Fileurs	11½	3	—	3	—	—	—	—	—	—	—	—	—	—	—
	Séranceurs	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	TOTAUX GÉNÉRAUX (Chanvre, filatures)	—	67	—	65	1	1	—	—	—	—	—	—	—	—	—
4454	Dévideurs	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	id.	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	TOTAUX GÉNÉRAUX (Chanvre, peignages)	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
4455	Cardeurs	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	Fileuses, dévideuses et épouleuses	11½	35	—	35	—	—	—	—	—	—	—	—	—	—	—
	Fileuses (aides)	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	Séparateurs de jute	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	Forgerons et graisseurs	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	Magasiniers	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
4456	Cardeurs	11	5	—	5	—	—	—	—	—	—	—	—	—	—	—
	Fileuses	11	5	—	5	—	—	—	—	—	—	—	—	—	—	—
	id. (apprenties)	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—

Sources: Office du Travail (1896), volume XII, pages 2-3

D.2. Maximum likelihood estimates

If there are n_i observations in a wage interval $[w_i^l, w_i^h]$, we can write the following log likelihood function:

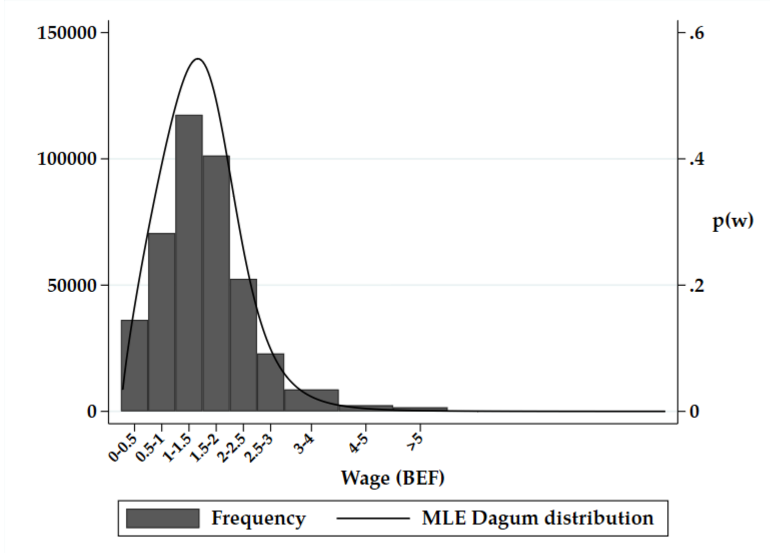
$$\mathcal{L}(\theta|w) = \sum_i n_i log(F_\theta(w_i^h) - F_\theta(w_i^l)).$$

with $F_\theta(\cdot)$ an assumed parametric function of a probability distribution with parameters θ. Maximizing the log likelihood function gives $\hat{\theta}$, which allows us to impute percentiles and inequality measures.

Figure D5 presents the published interval-censored data alongside the fitted Dagum wage distributions for the entire male factory population in both 1846 and 1896. Figure D5 further illustrates the similarity of ML estimates for the Dagum, Singh-Maddala and GB2 distributions.

FIGURE D5. Distribution of male daily wages in 1846 and 1896

A. 1846



B. 1896

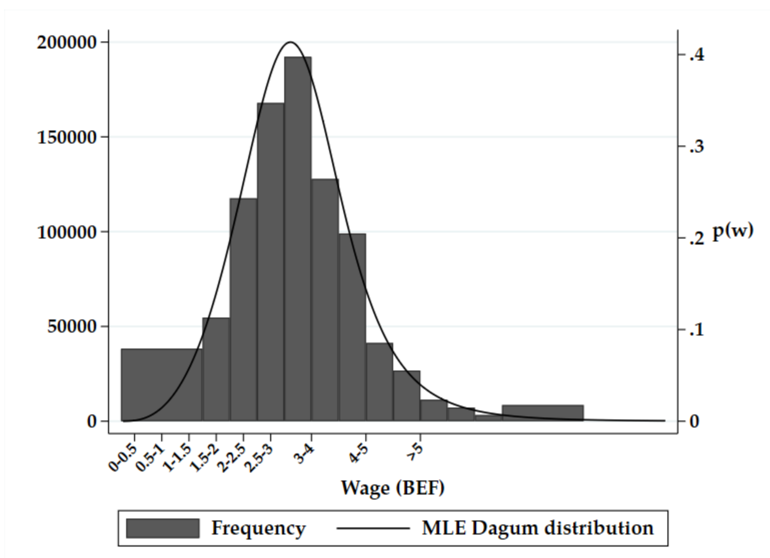
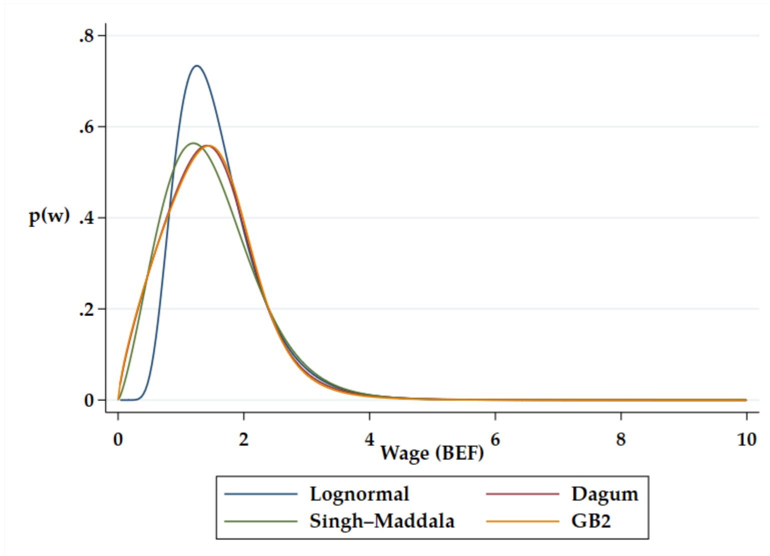
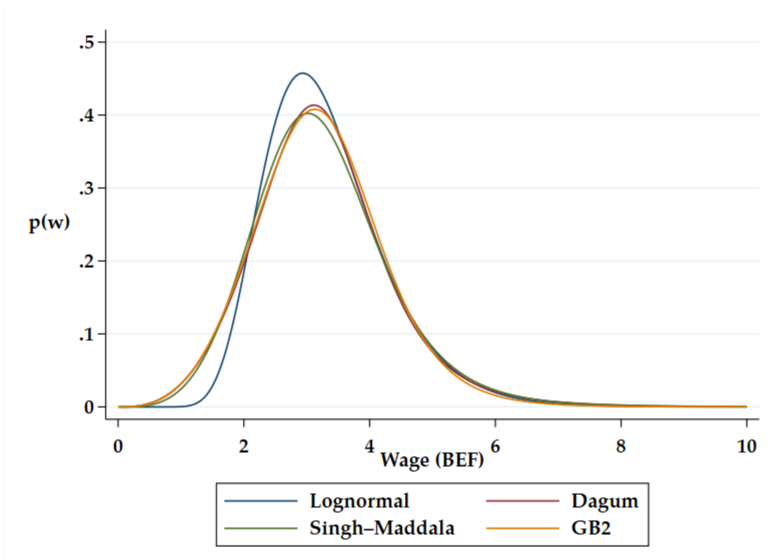


FIGURE D6. Different parametric forms for male daily wages in 1846 and 1896

A. 1846



B. 1896



Appendix E. Overview of sample sizes

Table E1. Overview of sample sizes across different models in main text and appendix

Model	Sample selection	Number of observations (N)	
a) Main text			
Figure 6(A) and Table F1	Base sample in logs	320	(industry-district)
Figure 6(B) and Table F2	Base sample in logs	320	(industry-district)
Figure 8(A) and Table G3	Base sample in log-differences	160	(industry-district)
Figure 8(B) and Table G4	Export/capita available	156	(industry-district)
b) Appendix (robustness)			
Figure F1(A) and Table F3	MLE available	150	(industry-province)
Figure F1(B) and Table F4	Full sample in levels	1212	(industry-district)
Figure F1(C) and Table F5	Base sample in logs	320	(industry-district)
Figure F1(D) and Table F6	MLE available	150	(industry-province)
Figure F1(E) and Table F7	Full sample in levels	1212	(industry-district)
Figure 8(A) and Table G5	Base sample in log-differences	160	(industry-district)
Figure 8(B) and Table G6	Export/capita available	156	(industry-district)

Appendix F. TWFE estimates

In this section, we provide more information on our Instrumental Variables (IV) approach as well as alternative specifications. This section is structured as following:

- Section F.1 presents the estimates of σ and β under alternative specifications.
- Section F.2 presents the tables underlying the IV estimates of the main text as well as the alternative specifications.

We provide several alternative specifications to assess the robustness of our findings that 19th-century steam technology affected wage inequality negatively. First, we replace the dependent variable in Equation (17) from our 'naive' midpoint-based appraisals of the respective percentiles by the maximum likelihood estimates (MLE) thereof, as discussed in Section 4.3. This exercise is performed at the industry-province level, rather than at the industry-district level. Figure F1(A) and Figure F1(B) show the robustness of our results, without and with a control for trade intensity per worker respectively.

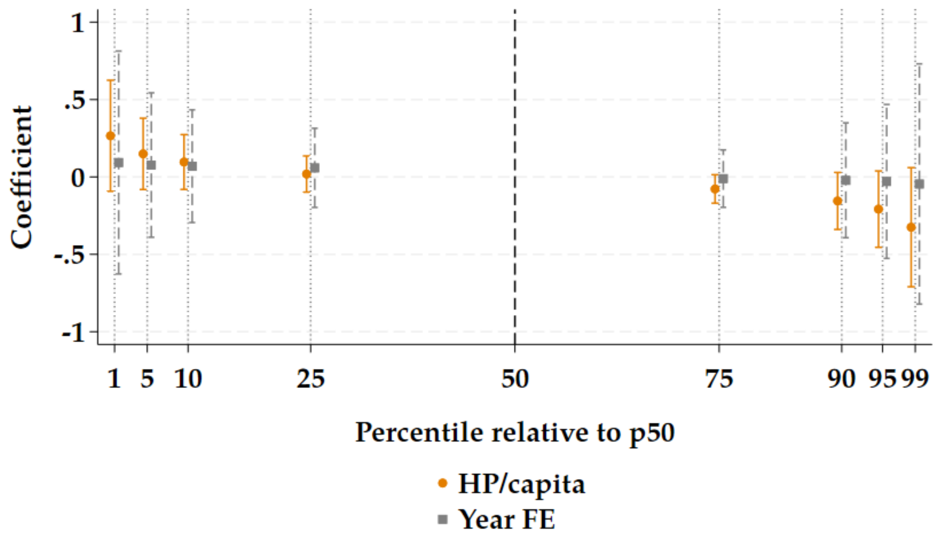
Second, we also present the estimation of Equation (17) in levels, rather than in logs. This is to ensure that we do not impose sample bias by selecting only non-zero observations. This is important, as our horsepower per capita in 1846 contains many zeros, given the limited state of mechanization in 1846 as well as the high level of disaggregation of our data at the industry-district level. Figure F1(C) shows how the key stylized fact of decreasing wage inequality, and the relationship with the horsepower variable remains intact. A difference is, however, that the reduction in wage inequality in levels is mostly driven by comparatively slower wage growth at the higher ends of the wage distribution compared to the median.

Next, we assess whether our results also hold for the wider population of adult workers. We do so using both our 'naive' midpoint-based and MLE-based estimates of percentiles of the adult wage distribution. The estimates $\hat{\beta}$ and $\hat{\gamma}$ for both approaches can be seen in Figure F1(C) and Figure F1(D) respectively. In Figure F1(E), we again estimate Equation (17) in levels (without log transformation) and find a pattern similar to when analyzing the male-workers sample in Figure F1(C).

F.1. Alternative specifications

FIGURE F1. Estimates of γ and β (robustness)

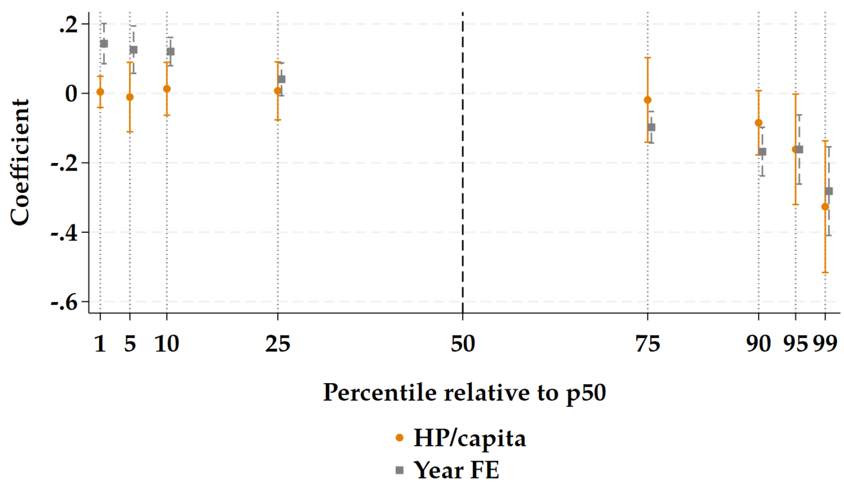
A. Male workers (MLE), industry-province level



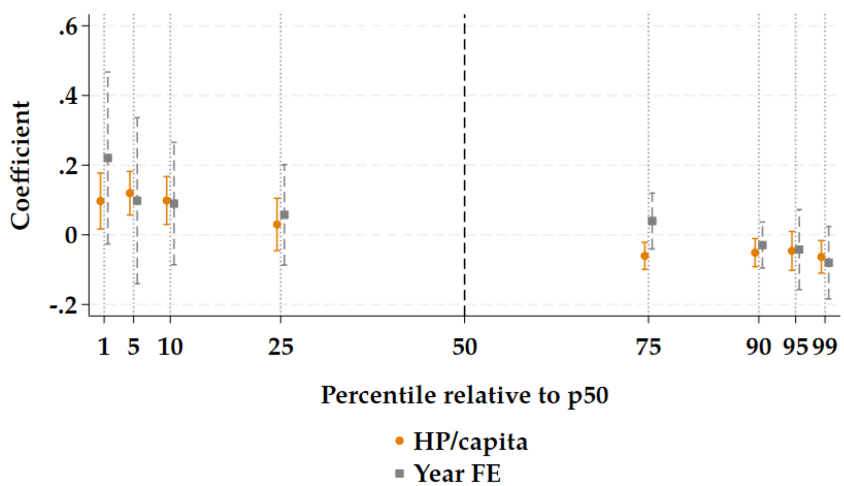
Notes: The regressions are weighted using the employment shares. Block-bootstrapped at the industry-province level (panel A). More details can be found in Table F3 (panel A).

Estimates of γ and β (robustness) - continued

B. Male workers, no logs, industry-district level



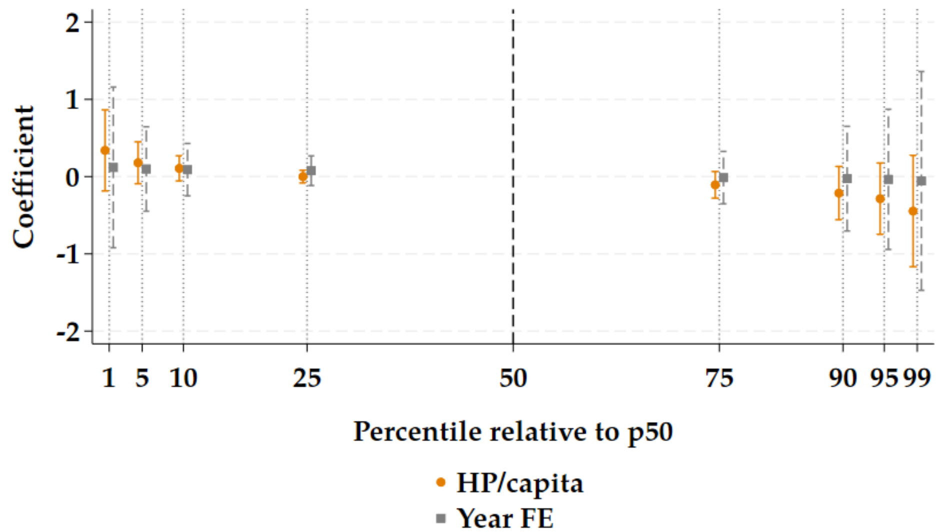
C. Adult workers, industry-district level



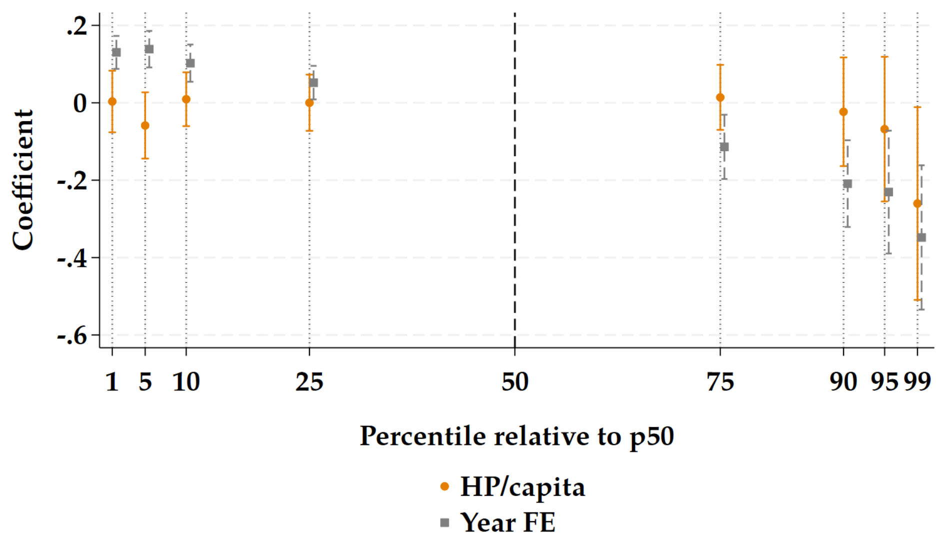
Notes: The regressions are weighted using the employment shares. Clustered standard errors at the district level (panel A and B). More details can be found in Table F4 (panel A) and Table F5 (panel B) in Appendix F.2.

Estimates of γ and β (robustness) - continued

D. Adult workers (MLE), industry-province level



E. Adult workers, no logs, industry-province level



Notes: The regressions are weighted using the employment shares. Block-bootstrapped at the industry-province level (panel A). Clustered standard errors at the district level (panel B). More details can be found in Table F6 (panel A) and Table F7 (panel B) in Appendix F.2.

F.2. Tables of main and alternative specifications

Table F1. **TWFE (levels), male workers**

	Independent variables				
Percentile	**Variable**	**Coef.**	**SE**	R^2	**N**
1	ln(Horsepower per capita)	0.254	(0.053)	0.827	320
	I(year=1896)	0.702	(0.154)		
	Constant	-0.057	(0.149)		
5	ln(Horsepower per capita)	0.217	(0.031)	0.810	320
	I(year=1896)	0.646	(0.086)		
	Constant	0.228	(0.070)		
10	ln(Horsepower per capita)	0.142	(0.045)	0.836	320
	I(year=1896)	0.756	(0.078)		
	Constant	0.210	(0.092)		
25	ln(Horsepower per capita)	0.109	(0.027)	0.875	320
	I(year=1896)	0.615	(0.058)		
	Constant	0.536	(0.064)		
50	ln(Horsepower per capita)	0.086	(0.035)	0.900	320
	I(year=1896)	0.579	(0.072)		
	Constant	0.749	(0.084)		
75	ln(Horsepower per capita)	0.071	(0.021)	0.925	320
	I(year=1896)	0.539	(0.046)		
	Constant	0.980	(0.052)		
90	ln(Horsepower per capita)	0.060	(0.011)	0.924	320
	I(year=1896)	0.510	(0.027)		
	Constant	1.153	(0.028)		
95	ln(Horsepower per capita)	0.046	(0.010)	0.907	320
	I(year=1896)	0.530	(0.022)		
	Constant	1.222	(0.023)		
99	ln(Horsepower per capita)	0.049	(0.010)	0.879	320
	I(year=1896)	0.452	(0.020)		
	Constant	1.496	(0.020)		

Notes: The regressions are weighted according the district share in employment over both periods. Clustered standard errors (in parentheses) at the district level. The 'Percentile' column indicates the dependent variable, the respective percentiles.

TABLE F2. TWFE (relative), male workers

	Independent variables				
Percentile	**Variable**	**Coef.**	**SE**	R^2	**N**
1	ln(Horsepower per capita)	0.168	(0.034)	0.581	320
	I(year=1896)	0.123	(0.114)		
	Constant	-0.806	(0.101)		
5	ln(Horsepower per capita)	0.132	(0.035)	0.429	320
	I(year=1896)	0.067	(0.085)		
	Constant	-0.521	(0.078)		
10	ln(Horsepower per capita)	0.057	(0.040)	0.533	320
	I(year=1896)	0.177	(0.085)		
	Constant	-0.539	(0.090)		
25	ln(Horsepower per capita)	0.024	(0.026)	0.231	320
	I(year=1896)	0.036	(0.055)		
	Constant	-0.212	(0.061)		
75	ln(Horsepower per capita)	-0.015	(0.023)	0.585	320
	I(year=1896)	-0.040	(0.042)		
	Constant	0.231	(0.050)		
90	ln(Horsepower per capita)	-0.026	(0.028)	0.623	320
	I(year=1896)	-0.068	(0.054)		
	Constant	0.404	(0.065)		
95	ln(Horsepower per capita)	-0.040	(0.039)	0.575	320
	I(year=1896)	-0.049	(0.084)		
	Constant	0.473	(0.096)		
99	ln(Horsepower per capita)	-0.037	(0.037)	0.638	320
	I(year=1896)	-0.127	(0.080)		
	Constant	0.747	(0.091)		

Notes: The regressions are weighted according the district share in employment over both periods. Clustered standard errors (in parentheses) at the district level. The 'Percentile' column indicates the dependent variable, which compares the respective percentiles to the median ($p50$).

TABLE F3. **TWFE (relative), male workers (MLE)**

	Independent variables				
Percentile	**Variable**	**Coef.**	**SE**	R^2	**N**
1	ln(Horsepower per capita)	0.266	(0.185)	0.713	150
	I(year=1896)	0.093	(0.341)		
	Constant	-1.151	(0.458)		
5	ln(Horsepower per capita)	0.149	(0.115)	0.702	150
	I(year=1896)	0.077	(0.218)		
	Constant	-0.785	(0.294)		
10	ln(Horsepower per capita)	0.096	(0.085)	0.683	150
	I(year=1896)	0.069	(0.170)		
	Constant	-0.620	(0.232)		
25	ln(Horsepower per capita)	0.019	(0.052)	0.545	150
	I(year=1896)	0.058	(0.124)		
	Constant	-0.377	(0.180)		
75	ln(Horsepower per capita)	-0.078	(0.050)	0.717	150
	I(year=1896)	-0.011	(0.092)		
	Constant	0.243	(0.125)		
90	ln(Horsepower per capita)	-0.155	(0.099)	0.717	150
	I(year=1896)	-0.022	(0.183)		
	Constant	0.487	(0.250)		
95	ln(Horsepower per capita)	-0.208	(0.133)	0.717	150
	I(year=1896)	-0.029	(0.245)		
	Constant	0.652	(0.335)		
99	ln(Horsepower per capita)	-0.325	(0.207)	0.717	150
	I(year=1896)	-0.046	(0.383)		
	Constant	1.018	(0.524)		

Notes: The regressions are weighted according the district share in employment over both periods. Clustered standard errors (in parentheses) at the district level. The 'Percentile' column indicates the dependent variable, which compares the respective percentiles to the median ($p50$).

TABLE F4. **TWFE (relative), male workers, no logs**

	Independent variables				
Percentile	**Variable**	**Coef.**	**SE**	R^2	**N**
1	Horsepower per capita	0.004	(0.023)	0.532	1212
	I(year=1896)	0.143	(0.030)		
	Constant	0.334	(0.013)		
5	Horsepower per capita	-0.011	(0.051)	0.411	1212
	I(year=1896)	0.126	(0.035)		
	Constant	0.471	(0.019)		
10	Horsepower per capita	0.013	(0.039)	0.545	1212
	I(year=1896)	0.120	(0.021)		
	Constant	0.545	(0.014)		
25	Horsepower per capita	0.007	(0.043)	0.195	1212
	I(year=1896)	0.041	(0.024)		
	Constant	0.780	(0.013)		
75	Horsepower per capita	-0.019	(0.062)	0.635	1212
	I(year=1896)	-0.098	(0.023)		
	Constant	1.352	(0.025)		
90	Horsepower per capita	-0.085	(0.047)	0.628	1212
	I(year=1896)	-0.168	(0.036)		
	Constant	1.672	(0.023)		
95	Horsepower per capita	-0.161	(0.081)	0.600	1212
	I(year=1896)	-0.162	(0.051)		
	Constant	1.858	(0.034)		
99	Horsepower per capita	-0.327	(0.097)	0.629	1212
	I(year=1896)	-0.282	(0.065)		
	Constant	2.434	(0.046)		

Notes: The regressions are weighted according the district share in employment over both periods. Clustered standard errors (in parentheses) at the district level. The 'Percentile' column indicates the dependent variable, which compares the respective percentiles to the median ($p50$).

TABLE F5. TWFE (relative), adult workers

	Independent variables				
Percentile	Variable	Coef.	SE	R^2	N
1	ln(Horsepower per capita)	0.097	(0.041)	0.522	320
	I(year=1896)	0.221	(0.126)		
	Constant	-0.969	(0.125)		
5	ln(Horsepower per capita)	0.120	(0.032)	0.468	320
	I(year=1896)	0.098	(0.122)		
	Constant	-0.621	(0.105)		
10	ln(Horsepower per capita)	0.099	(0.035)	0.471	320
	I(year=1896)	0.090	(0.090)		
	Constant	-0.482	(0.091)		
25	ln(Horsepower per capita)	0.030	(0.038)	0.364	320
	I(year=1896)	0.057	(0.074)		
	Constant	-0.280	(0.100)		
75	ln(Horsepower per capita)	-0.061	(0.020)	0.565	320
	I(year=1896)	0.040	(0.041)		
	Constant	0.116	(0.052)		
90	ln(Horsepower per capita)	-0.051	(0.021)	0.687	320
	I(year=1896)	-0.029	(0.034)		
	Constant	0.383	(0.050)		
95	ln(Horsepower per capita)	-0.046	(0.028)	0.695	320
	I(year=1896)	-0.043	(0.059)		
	Constant	0.497	(0.076)		
99	ln(Horsepower per capita)	-0.063	(0.024)	0.757	320
	I(year=1896)	-0.080	(0.053)		
	Constant	0.739	(0.065)		

Notes: The regressions are weighted according the district share in employment over both periods. Clustered standard errors (in parentheses) at the district level. The 'Percentile' column indicates the dependent variable, which compares the respective percentiles to the median ($p50$).

TABLE F6. **TWFE (relative), adult workers (MLE)**

	Independent variables				
Percentile	**Variable**	**Coef.**	**SE**	R^2	**N**
1	ln(Horsepower per capita)	0.339	(0.287)	0.717	150
	I(year=1896)	0.119	(0.490)		
	Constant	-1.289	(0.669)		
5	ln(Horsepower per capita)	0.179	(0.147)	0.748	150
	I(year=1896)	0.099	(0.248)		
	Constant	-0.881	(0.341)		
10	ln(Horsepower per capita)	0.106	(0.087)	0.773	150
	I(year=1896)	0.090	(0.150)		
	Constant	-0.697	(0.207)		
25	ln(Horsepower per capita)	-0.000	(0.046)	0.467	150
	I(year=1896)	0.076	(0.107)		
	Constant	-0.425	(0.148)		
75	ln(Horsepower per capita)	-0.107	(0.095)	0.670	150
	I(year=1896)	-0.013	(0.167)		
	Constant	0.271	(0.227)		
90	ln(Horsepower per capita)	-0.213	(0.191)	0.670	150
	I(year=1896)	-0.027	(0.333)		
	Constant	0.543	(0.455)		
95	ln(Horsepower per capita)	-0.286	(0.256)	0.670	150
	I(year=1896)	-0.036	(0.447)		
	Constant	0.728	(0.610)		
99	ln(Horsepower per capita)	-0.446	(0.399)	0.670	150
	I(year=1896)	-0.056	(0.697)		
	Constant	1.136	(0.952)		

Notes: The regressions are weighted according the district share in employment over both periods. Clustered standard errors (in parentheses) at the district level. The 'Percentile' column indicates the dependent variable, which compares the respective percentiles to the median ($p50$).

TABLE F7. TWFE (relative), adult workers, no logs

	Independent variables				
Percentile	Variable	Coef.	SE	R^2	N
1	Horsepower per capita	0.003	(0.041)	0.599	1212
	I(year=1896)	0.130	(0.022)		
	Constant	0.336	(0.014)		
5	Horsepower per capita	-0.059	(0.044)	0.494	1212
	I(year=1896)	0.139	(0.024)		
	Constant	0.445	(0.016)		
10	Horsepower per capita	0.009	(0.035)	0.476	1212
	I(year=1896)	0.102	(0.025)		
	Constant	0.523	(0.015)		
25	Horsepower per capita	0.000	(0.037)	0.277	1212
	I(year=1896)	0.052	(0.022)		
	Constant	0.740	(0.010)		
75	Horsepower per capita	0.014	(0.043)	0.543	1212
	I(year=1896)	-0.114	(0.042)		
	Constant	1.369	(0.019)		
90	Horsepower per capita	-0.023	(0.072)	0.574	1212
	I(year=1896)	-0.209	(0.057)		
	Constant	1.767	(0.022)		
95	Horsepower per capita	-0.068	(0.095)	0.577	1212
	I(year=1896)	-0.231	(0.081)		
	Constant	1.975	(0.025)		
99	Horsepower per capita	-0.260	(0.127)	0.668	1212
	I(year=1896)	-0.348	(0.095)		
	Constant	2.643	(0.047)		

Notes: The regressions are weighted according the district share in employment over both periods. Clustered standard errors (in parentheses) at the district level. The 'Percentile' column indicates the dependent variable, which compares the respective percentiles to the median ($p50$).

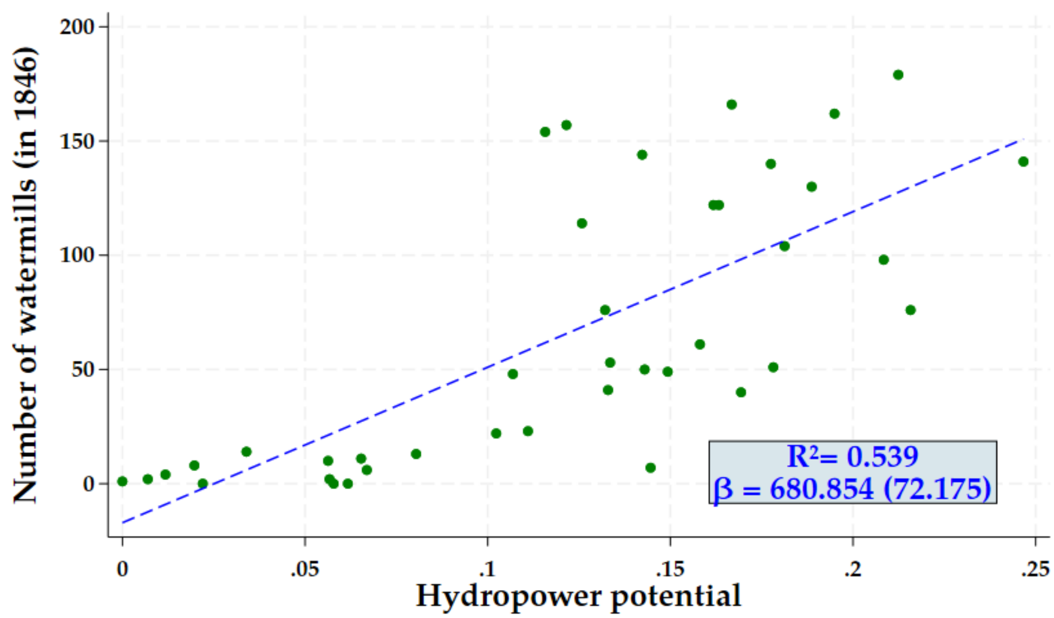
Appendix G. IV estimates

In this section, we provide more information on our Instrumental Variables (IV) approach as well as alternative specifications. This section is structured as following:

- Section G.1 presents more background information and the details behind the first-stage estimates.
- Section G.2 presents the estimates of β under alternative specifications.
- Section G.3 presents the tables underlying the IV estimates of the main text as well as the alternative specifications.

G.1. Instruments and first-stage estimates

FIGURE G1. Hydropower potential and watermills in 1846



Notes: Hydropower potential is calculated as the number of potential hydropower locations per km^2 within a district.

TABLE G1. First-stage of 2SLS procedure in Figure 8, male workers

IV approach	Variable	Coef.	SE	R^2	F-stat	N
1) Coal	Coal presence	-0.019	(0.002)	0.276	90.625	160
	Constant	2.238	(0.084)			
2) Hydro	Hydro potential	-8.934	(1.178)	0.172	57.517	160
	Constant	2.803	(0.197)			
3) Vector	Coal presence	-0.015	(0.002)	0.284	98.820	160
	Hydro potential	-2.982	(1.114)			
	Constant	2.531	(0.130)			

Notes: The regressions are weighted according the district share in employment over both periods. Clustered standard errors (in parentheses) at the district level.

TABLE G2. First-stage of 2SLS procedure in Figure G2, adult workers

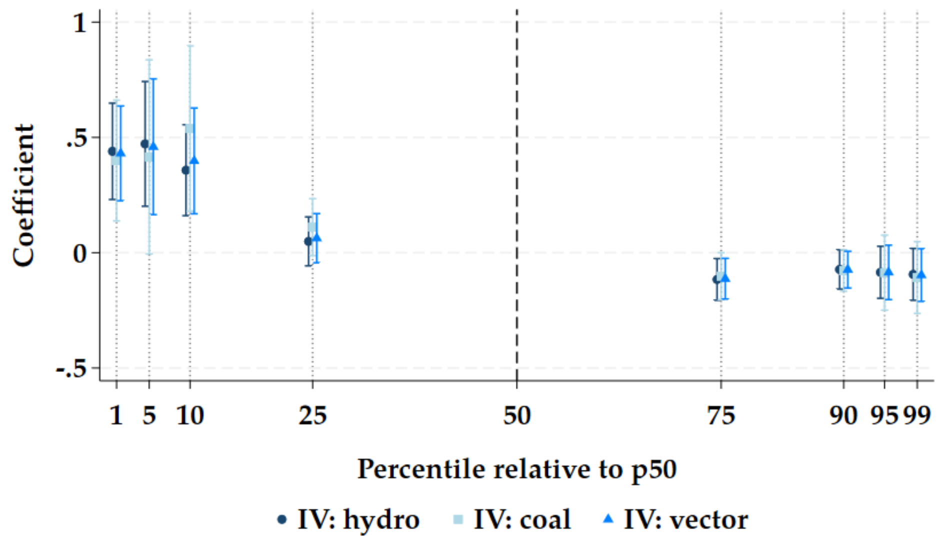
IV approach	Variable	Coef.	SE	R^2	F-stat	N
1) Coal	Coal presence	-0.019	(0.002)	0.276	90.625	160
	Constant	2.238	(0.084)			
2) Hydro	Hydro potential	-8.934	(1.178)	0.172	57.517	160
	Constant	2.803	(0.197)			
3) Vector	Coal presence	-0.015	(0.002)	0.284	98.820	160
	Hydro potential	-2.982	(1.114)			
	Constant	2.531	(0.130)			

Notes: The regressions are weighted according the district share in employment over both periods. Clustered standard errors (in parentheses) at the district level.

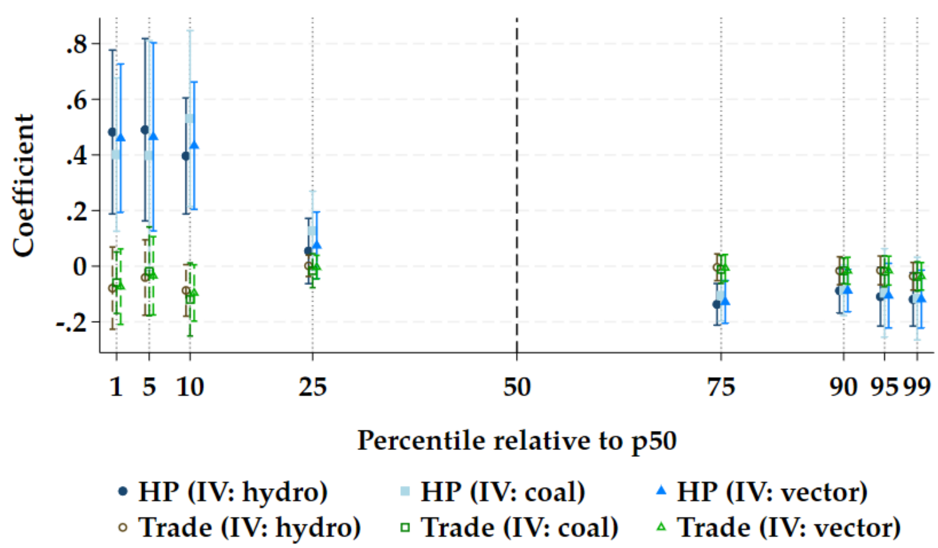
G.2. Alternative specifications

FIGURE G2. IV estimates of β, adult workers

A. Using Equation (18)



B. Augmenting Equation (18) with exports per worker



Notes: The regressions are weighted using the employment shares. Clustered standard errors at the district level. More details can be found in Table G5 (panel A) and Table G6 (panel B) in Appendix G.3. The first-stage estimates can be found in Table G2 in Appendix G.1.

G.3. Tables of main and alternative specifications

TABLE G3. IV, male workers

		Independent var.				Hansen test	
		HP/cap.					
IV	Percentile	Coef.	SE	N	F-stat	J	(p)
a) Coal presence	1	0.410	(0.074)	160	90.625		
	5	0.394	(0.075)				
	10	0.220	(0.085)				
	25	0.104	(0.037)				
	75	-0.027	(0.045)				
	90	-0.021	(0.039)				
	95	-0.079	(0.057)				
	99	-0.069	(0.054)				
b) Hydro potential	1	0.352	(0.066)	160	57.517		
	5	0.429	(0.109)				
	10	0.412	(0.135)				
	25	0.119	(0.057)				
	75	-0.079	(0.077)				
	90	-0.048	(0.071)				
	95	-0.087	(0.096)				
	99	-0.051	(0.082)				
c) Vector	1	0.398	(0.069)	160	98.820	0.839	(p= 0.360)
	5	0.401	(0.077)			0.191	(p= 0.662)
	10	0.258	(0.096)			3.843	(p= 0.050)
	25	0.107	(0.039)			0.142	(p= 0.706)
	75	-0.037	(0.047)			0.977	(p= 0.323)
	90	-0.026	(0.042)			0.364	(p= 0.546)
	95	-0.080	(0.062)			0.018	(p= 0.893)
	99	-0.065	(0.057)			0.098	(p= 0.754)

Notes: The regressions are weighted according the district share in employment over both periods. Clustered standard errors (in parentheses) at the district level. The 'Vector' instrumental variable includes both coal presence and hydro potential as instruments. The 'Percentile' column indicates the dependent variable, which compares the respective percentiles to the median ($p50$).

TABLE G4. **IV, male workers, augmented with trade**

		Independent var.							
		HP/cap.		Export/cap.				Hansen test	
IV	**Percentile**	**Coef.**	**SE**	**Coef.**	**SE**	**N**	***F*-stat**	*J*	(p)
a) Coal presence	1	0.449	(0.099)	-0.027	(0.054)	156	58.637		
	5	0.410	(0.091)	-0.066	(0.060)				
	10	0.255	(0.074)	-0.089	(0.034)				
	25	0.117	(0.046)	-0.027	(0.013)				
	75	-0.043	(0.044)	-0.004	(0.021)				
	90	-0.030	(0.042)	-0.034	(0.025)				
	95	-0.103	(0.057)	-0.019	(0.025)				
	99	-0.093	(0.059)	-0.044	(0.021)				
b) Hydro potential	1	0.350	(0.065)	-0.005	(0.041)	156	62.008		
	5	0.417	(0.101)	-0.068	(0.062)				
	10	0.409	(0.108)	-0.123	(0.053)				
	25	0.138	(0.071)	-0.032	(0.016)				
	75	-0.085	(0.075)	0.005	(0.027)				
	90	-0.056	(0.074)	-0.028	(0.026)				
	95	-0.097	(0.095)	-0.020	(0.028)				
	99	-0.057	(0.080)	-0.052	(0.022)				
c) Vector	1	0.424	(0.087)	-0.022	(0.050)	156	68.353	1.633	(p= 0.201)
	5	0.412	(0.087)	-0.067	(0.060)			0.006	(p= 0.938)
	10	0.294	(0.082)	-0.098	(0.038)			3.547	(p= 0.060)
	25	0.122	(0.051)	-0.028	(0.013)			0.192	(p= 0.662)
	75	-0.054	(0.046)	-0.002	(0.022)			0.609	(p= 0.435)
	90	-0.036	(0.045)	-0.032	(0.024)			0.264	(p= 0.608)
	95	-0.102	(0.063)	-0.019	(0.025)			0.010	(p= 0.919)
	99	-0.084	(0.061)	-0.046	(0.021)			0.355	(p= 0.552)

Notes: The regressions are weighted according the district share in employment over both periods. Clustered standard errors (in parentheses) at the district level. The 'Vector' instrumental variable includes both coal presence and hydro potential as instruments. The 'Percentile' column indicates the dependent variable, which compares the respective percentiles to the median ($p50$).

TABLE G5. **IV, adult workers**

IV	Percentile	Independent var. Coef.	SE	N	F-stat	Hansen test J	(p)
a) Coal presence	1	0.440	(0.107)	160	40.093		
	5	0.472	(0.138)				
	10	0.358	(0.101)				
	25	0.049	(0.054)				
	75	-0.116	(0.046)				
	90	-0.073	(0.043)				
	95	-0.085	(0.058)				
	99	-0.094	(0.057)				
b) Hydro potential	1	0.400	(0.134)	160	28.242		
	5	0.415	(0.215)				
	10	0.539	(0.183)				
	25	0.111	(0.063)				
	75	-0.102	(0.052)				
	90	-0.077	(0.046)				
	95	-0.087	(0.083)				
	99	-0.108	(0.079)				
c) Vector	1	0.431	(0.105)	160	32.235	0.163	(p= 0.686)
	5	0.459	(0.150)			0.162	(p= 0.687)
	10	0.398	(0.117)			2.280	(p= 0.131)
	25	0.063	(0.054)			0.972	(p= 0.324)
	75	-0.113	(0.045)			0.128	(p= 0.720)
	90	-0.074	(0.041)			0.014	(p= 0.906)
	95	-0.085	(0.060)			0.001	(p= 0.976)
	99	-0.097	(0.058)			0.060	(p= 0.807)

Notes: The regressions are weighted according the district share in employment over both periods. Clustered standard errors (in parentheses) at the district level. The 'Vector' instrumental variable includes both coal presence and hydro potential as instruments. The 'Percentile' column indicates the dependent variable, which compares the respective percentiles to the median ($p50$).

TABLE G6. IV, adult workers, augmented with trade

		Independent var.				Hansen test	
IV	**Percentile**	**Coef.**	**SE**	**N**	***F*-stat**	*J*	(p)
a) Coal presence	1	0.482	(0.150)	156	26.018		
	5	0.490	(0.167)				
	10	0.396	(0.106)				
	25	0.054	(0.060)				
	75	-0.137	(0.038)				
	90	-0.088	(0.041)				
	95	-0.110	(0.054)				
	99	-0.119	(0.049)				
b) Hydro potential	1	0.401	(0.141)	156	28.177		
	5	0.398	(0.211)				
	10	0.531	(0.161)				
	25	0.127	(0.072)				
	75	-0.105	(0.047)				
	90	-0.087	(0.046)				
	95	-0.096	(0.081)				
	99	-0.116	(0.076)				
c) Vector	1	0.460	(0.136)	156	22.564	0.456	(p= 0.500)
	5	0.465	(0.173)			0.395	(p= 0.530)
	10	0.433	(0.117)			1.552	(p= 0.213)
	25	0.075	(0.061)			1.119	(p= 0.290)
	75	-0.128	(0.039)			0.806	(p= 0.369)
	90	-0.088	(0.039)			0.001	(p= 0.973)
	95	-0.106	(0.059)			0.067	(p= 0.796)
	99	-0.119	(0.053)			0.003	(p= 0.954)

Notes: The regressions are weighted according the district share in employment over both periods. Clustered standard errors (in parentheses) at the district level. The 'Vector' instrumental variable includes both coal presence and hydro potential as instruments. The 'Percentile' column indicates the dependent variable, which compares the respective percentiles to the median ($p50$).