Industry Contribution to US Wage Inequality

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Abstract

Industry dimension is increasingly dominant to investigate the upward trend of inequality. This paper examines the key drivers of US wage inequality through a general equilibrium model, emphasising the role of heterogeneous capital-labour substitution elasticities across industries and of labour market concentration in shaping wage dispersion. Findings suggest that industry-level transformations on the labour side – *i.e.*, differentials in job tasks substitutability and workforce composition – constitute the principal drivers of real wage inequality. A structural estimation of the model reveals that trend-differences in the elasticities of substitution between ICT capital, routine and non-routine workers account for 94% of observed wage variance, while stronger sorting and segregation effects further exacerbate such dispersion. Upon neutralising structural differences between industries, Skill-Biased Technological Change reckons merely 6–15% of the observed wage inequality.

Jel: E24, J31, J82, L16, O33

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Introduction

Wage inequality has been on the rise in United States over the last decades: since the late 1970s, top 1% (0.1%) real wages grew by 181.7% (353.9%), whereas a comparatively modest increase of merely 43.7% marked the bottom 90%; in addition, between 1980 and 2022, the 90/10 real wage percentile ratio rose from 4.2 to 5.7.[1]

Understanding the cause behind such turn is a secular challenge in economics. A large body of research has identified some key components that rationalize the increases in wage inequality. A first motive resorts in the employment polarization pattern towards high- and low-wage jobs driven by the return to skills.[2] However, under new consensus, polarization is rationalized by job tasks (*e.g.*, Autor, Katz, et al. 2006), and not by residual or skill-driven wage differentials.[3] Then, the centrality of the industry dimension: Haltiwanger et al. (2024) examine the contributions of worker, firm and industry components to total wage inequality, demonstrating how differences across industries quantitatively explain more than 60% of the increasing wage dispersion over the past 30 years. A comprehensive analysis of US inequality thus requires considering both workforce characteristics and industrial composition.

Addressing the issue, this paper identifies trend differences in industry-level capital-labour substitution elasticities as key drivers of real wage inequality, with labour side transformations from Skill-Biased Technological Change chiefly responsible for wage dispersion across industries. I build a general equilibrium model of structural transformations across industries differing in technological progress to investigate the key determinants of US wage inequality. Such differences manifest in the matter of technology adoption, either in terms of capital and labour endowments or as of heterogeneous technology parameters (*i.e.*, substitution elasticities among factors of production). Substitution degrees play an intuitively fundamental role on trends in factor shares: with "gross substitution" (values above 1), positive changes in capital endowments would increase the capital share of output thus reducing the marginal product of labour; opposite is "gross complementarity" (values below 1). Moreover, elasticity parameters are endogenous to changes in factors of production and, foremost, uneven trends of substitution elasticities across industries would lead to different magnitudes of changes in marginal products of an evolving technology.

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[1] Visit the reports by Epi (2024) and Fed (2024) to inspect these magnitudes, respectively.

[2] Shifts in the labour force composition in the matter of education and experience underwent a *job polarization* in the labour market, wherein rapid growth in both high and low education jobs has led to a reduction in the "middle skill" employment share (Acemoglu and Autor 2011). Although the supply of skilled workers has risen markedly, the skill-premium in wages has continued to grow. Central was the technology-based polarization hypothesis (Michaels et al. 2014, Burstein et al. 2019) and the theory of Skill Biased Technological Change (SBTC), where "a burst of new technology caused a rise in the demand for highly skilled workers, which in turn led to a rise in wage inequality" (Card and DiNardo 2002). Globalization (*e.g.*, Epifani and Gancia 2008) and new technologies fostered job polarization by directing workers toward the ends of the wage distribution, thereby contributing to inequality − since high- (low-) skill jobs tend to be high- (low-) paid.

[3] Providing a sectoral perspective, Cerina, Moro, et al. (2021) assert how the polarization towards the bottom of the distribution does depend by routine occupations, but it is crucially shaped by the types of sector (services and non-services sectors) rather than the performed job task content.

Inequality in wages can thus be influenced along two dimensions. Firstly, consider the case in which industries share the same substitution elasticities: disparities in the dynamics and allocation of capital and/or labour quantities would be the sole driver of widening inequality, thereby aligning with the perspective of Skill-Biased Technological Change (SBTC).[4] Conversely, uneven degrees of substitutability across industries would primarily impact inequality in the absence – or regardless – of changes in factor endowments differentials, especially when substitution elasticities evolve alongside shifts in capital and labour quantities. To build intuition, in the former case what matters the most is the different quantity accumulation rate: if, say, two industries would have the same change in inputs of production, then having the same substitution elasticities ensure that the wage effect is even. The latter case, instead, specifies how the same accumulation rate of capital and labour endowments would result, in any case, in uneven wage levels when industries have (significant) differences in their technology parameters, and thus wage dispersion is mostly driven by the "structure" of technical and technological progress.

Given these overlapping explanations, the undertaken quantitative analysis seeks to assess the relative importance of each of the aforementioned factors. While the first has been examined at length, largely unexplored remain the effects of structural transformations (hereafter interpreted as sectoral heterogeneous trends in the capital-labour substitution elasticities as in Alvarez-Cuadrado et al. 2018), and this paper is the first attempt to disentangle their contribution to wage inequality. I will demonstrate how, given the path of inputs of production, trend-differentials (both in the direction and in the magnitude) in the elasticities of substitution between capital and labour types account for a greater part of the observed between-industry wage variance across US industries. The analysis unfolds in five main parts. I begin by delivering a set of novel stylized facts on the relationship between Information and Communication Technology (ICT), labour force composition, and dispersion in real wages at 3-digit US 2017 NAICS industry level from 2003 to 2022.[5] Second, I provide a theoretical formalization of these findings introducing a structural model wherein wage inequality is a consequence of an interplay between evolving production technology, workforce composition, and labour market concentration (shaped by workers' sorting and segregation effects). Third, I bring the specified model to the data via an internal estimation of its parameters; once duly calibrated, I then conduct a battery of counterfactual exercises designed to isolate the contribution of changes in structural parameters to the observed variance in US real wages. Finally, I discuss how shifts in capital and labour endowments, as well as that in sectoral

[4] SBTC studies the interaction between technological advances and labour market outcomes, ascribing to computer and technological capital differentials the rise in wage inequality. In particular, there is a "skill-bias" in the dynamics of labour demand: new technologies benefit workers at the top of the skill distribution, while their adoption harms those at the bottom in the matter of being substituted; see Tinbergen (1974), Katz and Murphy (1992), Card and DiNardo (2002), or Acemoglu and Autor (2011), among others.

[5] I document the importance of structural transformations on US wage inequality: industries exhibiting the largest growth in real wages are those significantly adopting ICT in physical capital, and where the substitution of routine with non-routine workers is most pronounced.

productivity, fail to capture the observed level of wage inequality when structural differences across industries are removed.

To understand how differences in the industrial composition of capital and labour types affect wage dispersion, I build a general equilibrium model of industries differing in degrees of substitution among inputs of production. The market structure equips the economy with a block of industries populated by monopolistically competitive firms, while households are *ex-ante* divided in routine and non-routine job tasks. The latter are complementary to ICT capital while routine ones are substitutes, in the spirit of Krusell et al. (2000), and Skill Biased Technological Change (SBTC) is two-sided: advances in technology *directly* determines the share of non-routine workers along the stock of ICT capital, and *indirectly* (through job tasks' substitution) the measure of routines. As for heterogeneity, an important phenomena of the labour market is that workers are themselves of varying capacities depending on where they work; hence, in the model, households retain different productivities across workplaces and directly sort into the firm-industry pair maximizing their idiosyncratic efficiency in performing the correspondent job tasks. The resultant firm-related and upward-sloping labour supplies trace a mechanism establishing a direct connection of the wage premium with sorting and segregation effects, pondered by a not perfectly elastic labour supply in a perfectly competitive labour market.[6]

Quantitatively, I estimate the model on industry-level US data. The main structural parameters are two elasticities of substitution between both capital and worker categories, and the degree of labour market concentration.[7] Despite its convoluted structure, a transparent identification of the production complementarity parameters arises from the general equilibrium properties of the model: elasticities are estimated following the framework proposed by Karabarbounis and Neiman (2014), whose estimation is based on the labour share; I reverse their identification of cross-sectional variations by imposing a direct (negative) relationship between trends in labour share measures and relative ICT capital quantity, both measured at industry level. Capital-labour elasticities' estimates report "gross complementarity", with values ranging between 0.25 and 0.8, averaged across industries. Finally, in relation to sorting and segregation in the labour market, workers' concentration by job tasks among industries is proxied by the degree of dispersion in households productivities.

Given the estimated set of parameters, the model built is able to capture key features of the inter-industry wage structure and of inequality levels. At its baseline scenario, the performed calibration outlines a marked heterogeneity in cross-sectional values of the elasticities of substitution, with top industries (major vari-

[6] A genuine link of these labour supplies is with the class of "new monopsony models" (see Manning 2021), whose natural implication would be of allowing firms to have wage-setting power. Appendix D performs a simulation under wage-setting power and numerically shows how assuming monopsony power in wage formation does not alter the results on industry wage inequality, as suggested by Card, Rothstein, et al. (2024a).

[7] I am referring to the elasticity of substitution between routine and non-routine job tasks, and that between ICT capital and non-routine workers. Workers' concentration (diffusion) is intended to be the result of stronger (weaker) sorting and segregation effects.

ation in real wages) characterised by a prominent impact of technological change, followed by bottom (minor variation) and middle (intermediate variation) industries. A re-estimation procedure over two sub-periods confirms these differences in trends: technological parameters shifted unevenly across industries both in the direction and, most importantly, in magnitude; these joint shifts will be a crucial factor in explaining a substantial share of the between-industry wage inequality.[8] After having provided a reduced-form empirical evidence in support of the model's main theoretical implications, I employ the observed changes of these parameters at the heart of the counterfactual analysis, aimed at decomposing the industry component of US wage inequality since the early 2000s while allowing for the interaction between technological change, workforce composition and labour market concentration. To disentangle paramount channels, I first re-estimate the entire set of parameters over different time intervals, examining moment-differences in response to changes in single or combined parameters. Subsequently, I estimate sectoral productivities using industry-level production function, and evaluate their contribution, alongside changes in capital and labour quantities, when structural differences are precluded.

My main findings suggest that structural transformations of the US economy are the primary drivers of the observed wage inequality. Heterogeneous shifts in the degrees of substitution between capital and worker types at the industry level are central to address observed between-industry wage variance, and the paper allows to pin down four main takeaways. Firstly, separate variations in the two elasticities are insufficient to quantitatively capture the observed level of inequality; rather it is their combined shifts that explains most of the dispersion, accounting for 94% of US wage inequality in the data, and by 88% when aligning these changes with shifts in the industry-specific weights of factors of production. Substitutability across job tasks is crucial, while that between ICT capital and non-routine workers acts as a mitigating factor; in this context, rising wage inequality seems to be majorly impacted by the "worker-" rather than the "capital-side" of production. Stated differently, the *indirect component* of SBTC (*i.e.*, substitution across tasks) seems to be predominant rather than changes in non-routine workers along ICT capital; this well reconciles with the empirics, and with the contribution of capital and labour series on wage inequality, as inspected further below (fourth take-away). Secondly, these patterns, as well as that of workers' concentration, persist when considering between-industry inequality separately for routine and non-routine workers; trend-differences in technological parameters and changes in production inputs majorly hit the latter category.

Thirdly, considering increased labour market concentration alongside heterogeneous shifts in substitution elasticities, stronger workers sorting and segregation effects intensify total wage dispersion (98%). This outcome is a direct consequence of having included an upward-sloping labour supply curve, thus introducing an in-

[8] Industries where wages increased the most (less) have experienced a decrease in the complementarity between technological capital and non-routine workers of about 25% (131%), while slightly increasing the complementarity between job tasks of 3% (11%). Differently, intermediate industries undergone a reduction (20%) in substitutability of ICT capital-non-routine tuple, along a pale increase (3%) in job tasks substitution.

direct measure of residual wage inequality stemming from task-membership and workplace. As elaborated in Section 2, these are important factors characterizing wage inequality and, in the model, rising concentration is going to impact industries on their specific factor endowments, leading to a deterioration in their structural composition, and thereby generating divergent patterns in wage dynamics.

Fourthly, without any sort of trend-differences in technology parameters, I argue how SBTC approach tends to overestimate the actual variation in wage inequality. At the industry-level, most of the change is accounted by differentials in routine workers (and, generally, by employment) series, while combined variations in ICT capital and non-routine workers play a limited role in addressing wage inequality. Furthermore, in the absence of heterogeneous structural parameters across industries, changes in capital and labour quantities, as well as sectoral productivity, account for 6% to 15% of observed inequality. It appears that SBTC constitutes a necessary (but not sufficient) condition of wage variances; cross-sectional, dynamical, and trend differences in the rate of structural transformations across US industries are likely to primarily explain the between-industry component of wage inequality.

Related literature. The findings of this research are connected to several strands of the literature. First, the paper's main link is that with recent studies on wage inequality in US. Most of the attempts so far stress the pivotal importance of the role played by differences among individuals.[9] Although still contributing significantly to wage variance, the relevance of such *within-firm* dimension is declining. A burgeoning literature interpreted the rise in wage inequality from the mid-1970s notably driven by a *between-firm* dimension: dispersion across firms' average wages accounts for a vast fraction of total wage inequality growth.[10] Anyhow, recent evidence unveils that the differentials in firms' characteristics are primarily concentrated at the industry level. While the early literature on industries[11] suggested how inter-industry differences explains major wage premiums both for workers with the same skills and for the total variation in wages (Krueger and Summers 1988), and that the wage differential across US industries was high but stable for a considerable and vast part of the XX century (*e.g.*, Slichter 1950, Cullen 1956, Krueger and Summers 1988, Allen 1995),[12] the industry component of total wage inequality

[9] Interpretations on the *within-firm* dimension of inequality have been predominant (Eeckhout 2021), and a large body of empirics documented the role of individual characteristics on wage premium differentials. Early comprehensive explanations are Katz and Autor (1999) and Lemieux (2010), while noteworthy is the debate with "revisionists" who interpret rising differentials as episodic events; see Autor, Katz, et al. (2008).

[10] Firm differences are strong in several countries: Brazil (Alvarez et al. 2018), Germany (Card, Heining, et al. 2013), Italy (Bingley and Cappellari 2022), Portugal (Card, Cardoso, and Kline 2016), and US (Davis and Haltiwanger 1991, Dunne et al. 2004, Leonardi 2007, Barth et al. 2016, Song et al. 2019). Groshen (1991) studies the drivers of intra-industry variation of wages across firms.

[11] Refer to Krueger and Summers (1987) and Dickens and Katz (1987) for a discussion of the findings. A complementary literature explores the role of inter-industry dispersion in capital-labour ratios on wage inequality (Montgomery 1991, Caselli 1999), while sectoral differences are important also to interpret both the racial (Card, Rothstein, et al. 2024b) and the gender (Fields and Wolff 1995) pay gaps, and wage differentials under a behavioural economics perspective (Thaler 1989).

[12] Allen (2001) notices how the "stability" argument may be misleading since important within-industry fac-

has increased dramatically over the last 30 years.[13] Seminal in this sense is the work of Haltiwanger et al. (2024),[14] where wage differentials due to industrial factors are those in which the rise has been the largest over last decades, and pivotal is the role played by a small fraction of industries (similar results for Italy are handled by Briskar et al. 2022).[15] Significant industry wage premiums are also detected by Card, Rothstein, et al. (2024a): while these are positively associated with workers' skill sorting, their spatial composition (in terms of wage premiums and skill sorting) in local labour markets across selected and largest US commuting zones owns a modest role.[16] Building on this literature, I complement the on-going findings by focusing only on the industrial component of inequality. Theoretical models explaining the determinants of wage dispersion due to industry factors are missing: my contribution is to build a theory incorporating structural differences in the matter of substitutability of capital and labour endowments among US industries to address observed trends in between-industry wage inequality.[17]

Second, my analysis directly dives into the task-based literature.[18] The introduction of tasks in shaping wage inequality is due to Autor, Katz, et al. (2006), who stress how the dynamics governing the distribution of job task demands (due to technological evolution) is crucial for interpreting the hypothesis of *job polarization*. Technology and labour force composition is further analysed in Cortes et al. (2017), where technological advances cause a transition from routine into non-routine jobs. I

tors changes over time, while the constancy depends on a strong autocorrelation over a long time period. Under a cross-country comparisons, a substantial but stable inter-industry wage differential exists also among EU (Genre, Kohn, et al. 2011, Genre, Momferatou, et al. 2005) and OECD (Gittleman and Wolff 1993) countries.

[13] Rising between-industry wage inequality is a well documented fact (Davidson and Reich 1988, Bell and Freeman 1991, Howell and Wolff 1991, Allen 2001). Haltiwanger et al. (2024)'s contribution is to show its importance on the increase in total US wage inequality relative to both individual and firm components.

[14] Whose findings are reinforced by Haltiwanger et al. (2023) in a purely methodological contribution: while household-level data mostly provide worker-based explanation for wage inequality, administrative data emphasize the magnitude of firms and industries. Matching these two approaches in a unique Current Population Survey-Longitudinal Employer Household Dynamics (CPS-LEHD) dataset, authors detect how between-industry inequality owns most of the growth in US wage inequality. These conclusions lead to a bias in studies detecting humble (or negative) role of the industry differences component (*e.g.*, Hoffmann et al. 2020).

[15] Katz and Murphy (1992) notably observed that while shifts in labour demand across sectors play a relatively minor role, skill-intensive sectors contribute significantly to variations in workers' demand. Although not dominant, the between-industry composition of the workforce was already evident in their sample (1963-1987), preceding the period 1996-2018 examined by Haltiwanger et al. (2024).

[16] This paper focuses on the determinants of the US industry wage premium, rather than measuring inequality, and contributes to the literature on (un-)observable worker abilities (*e.g.*, Krueger and Summers 1988, Gibbons and Katz 1992, Gibbons, Katz, et al. 2005).

[17] Recent initial attempts for structural model identification are for firm-driven inequality (Kleinmann 2023 and Hong 2024 on spatial motives, Freund 2024 on worker complementarities). A link between firms' technology, recruitment behaviour, and wage inequality across education groups is in Macera and Tsujiyama (2024), while Erosa et al. (2025) interpret US labour market polarization and rising wage inequality as of changes in occupational sorting.

[18] Strong emphasis in measuring employment trends by job task content: rapid employment growth for non-routine tasks from early 1990s relative to routines (*e.g.*, Goos and Manning 2007, Goos, Manning, and Salomons 2009, Acemoglu and Autor 2011, Autor and Dorn 2013, Jaimovich and Siu 2020, Cerina, Moro, et al. 2021, Cerina, Dienesch, et al. 2023, Jaimovich, Zhang, et al. 2024, Siena and Zago 2024, Cossu et al. 2024).

exploit the division of labour into tasks to understand how the labour force composition, due to industry-driven technological change, contributes to US wage inequality.

Third, results build on studies that estimate the elasticity of substitution between capital and labour. I allude to two different strands of the literature that incorporate such estimation. The first refers to works that analyse the secular decline in the labour share[19] and, in particular, the role played by industries: Karabarbounis and Neiman (2014) detect how most of the decline of the labour share around the world occurs within industries and not due to changes in their size, Eden and Gaggl (2018) analyse the role of information and communication technology (ICT), Glover and Short (2023) rather focus on the role of demography in the decline of industry-level labour share. Secondly, this literature connects with that on structural transformations.[20] I point to Herrendorf, Herrington, et al. (2015), where differences in sectoral elasticities of substitution among capital and labour drive the reallocation of production factors across broadly defined sectors. These two lines overlap including the capital-labour elasticities (estimated at the industry level via the labour share) in a model incorporating wage inequality, mainly driven by the dispersion in the degrees of substitutability of both capital types and tasks' labour force across industries.

Finally, the literature on Skill-Biased-Technological-Change (SBTC) and wage inequality is an intersection. The theory provided in Krusell et al. (2000) – that accounts for trends in skill-premium, updated with new data by Ohanian et al. (2023) – is the reference point. I contribute to this framework by including sorting and segregation choices alongside the role of tasks to account for trends in wage inequality.

Roadmap. This introduction is succeeded by Section 1, which provides the motivating evidence at which the model presented in Section 2 refers to. Section 3 shows and assess the performance of the calibration strategy, while Section 4 quantifies the relevance of given parameters in accounting for the observed level of US wage inequality. Section 5 determines the importance of capital and labour quantities and of an estimated measure of sectoral productivity. Last section concludes.

1. Motivating evidence

To account for trends in wage dispersion I use annual US data, and the 3-digit US 2017 North American Industrial Classification System (NAICS) is adopted for the industry level definition. The (balanced) panel data built is due to the combination of two main different data sources: first, information on the stocks of physical and technological capital types are recovered from the Bureau of Economic Analysis (BEA),

[19] A myriad of explanations have been given to answer to this problem; see Karabarbounis (2024) for a comprehensive interpretation of the results, and Bergholt et al. (2022) for a notable shocks' decomposition.

[20] A growing debate studies the phenomenon of *structural transformation* (reallocation of economic activity across broadly defined sectors, namely agriculture, services and manufacturing) and its implications for economic aggregates. Early attempts are due to Matsuyama (2009) and Ray (2010), while Herrendorf, Rogerson, et al. (2014) provide a systematic review of the recent literature. Buera and Kaboski (2012) interprets the rising skill-premium in connection to the structural movement of economic activity toward services industries.

in the *Detailed Data for Fixed Assets* tables; the second source is the *Occupational Employment and Wage Statistics* (OEWS) program of the Bureau of Labor Statistics (BLS), which contains information on occupational employment and wage rates.

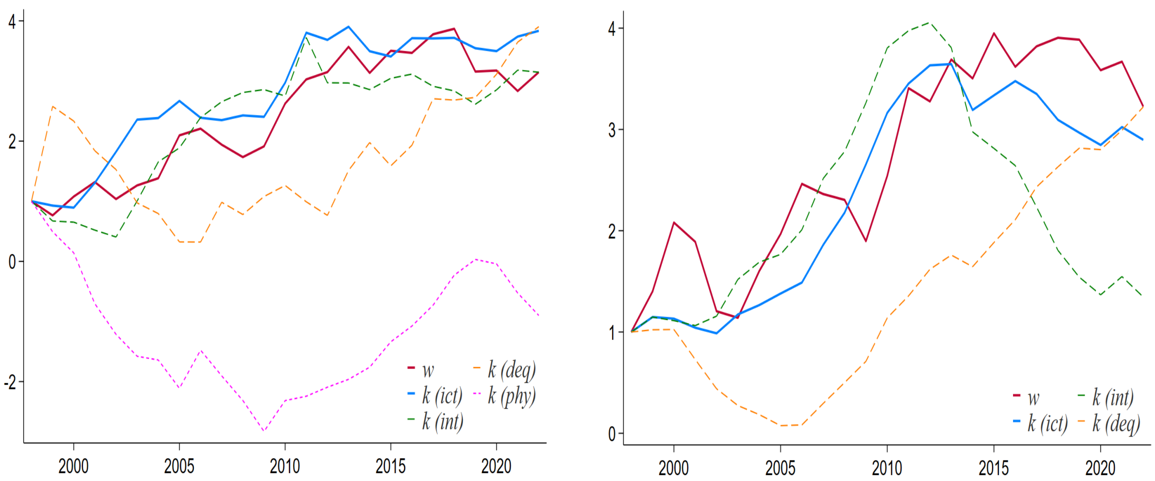
In each industry, among all the types of capital assets present in the former source of data, I am going to classify capital types accordingly: *digital equipment* comprises all the electronic structures that are useful to process technological issues; the stock of *intangible* capital coincides with that of "Total Intellectual Property Products" (IPP); finally, *physical* (or non-ICT) capital is the sum of all the remaining asset types, and the considered time window in the analysis on data from BEA only is 1998-2022. For what concerns data from BLS, information are provided for granular occupations according to the Standard Occupational Classification (SOC) for private 3-digit US 2017 NAICS industries from 2003 onwards. However, since detailed occupations may vary across industries, I exploit the labelling of "major" occupations and divide them in *routine* and *non-routine* tasks, to then merge these data with that extracted from BEA. In the merging process (BEA and BLS), the 4-digit industries in the BEA data have been clustered into 3-digit category, so that the main analysis is conducted on a complete sample of 62 private 3-digit US 2017 NAICS industries over an annual time window spanning from 2003 to 2022. See additional details and an extended discussion of the data in Appendix A.

1.1. US INDUSTRIES DIGITALIZATION

In addition to the aggregated capital types, I further define *ICT capital* to be the combination of intangibles and digital equipment. In addition, BEA collects data on wage levels of industries, together with total effective workforce; to focus on real wages, data on annual Consumer Price Index (CPI) inflation levels are extracted from FRED database. The time window considered throughout is 1998-2022, and both capital stocks and real wages are taken in industry per capita log-terms.

As a first step I shall detect whether differences in capital stocks among industries reflect differences in wages. To account for rising dispersion, Figure 1 plots the evolution of differentials in capital ratios and real wages. Panel 1a considers the industry-level dispersion as determined by the *inter-quartile range*, namely the distance between top and bottom 10% industries in each log-quantity: differences in these ratios are increasing over time when considering ICT capital, meaning that industries that have highest per worker ICT capital stock are widening the gap relative to those with the lowest one; same, but under alternate behaviour, is for paths related to intangible assets and digital equipment. Different story can be said for the stock of physical capital: over time, its gap among industries is declining, denoting a reduction of the distance in the stock of physical capital owned by each industry.

Comparing inter-industry differentials of each capital type with that of labour income, gaps in real wages are mainly related to gaps in ICT capital rather than other types of capital. The importance of *macro-complementarity* underlies this ob-



(A) INTERQUARTILE RANGE, 90^{th}-10^{th}

(B) *log*-VARIANCE

FIGURE 1: CROSS-INDUSTRY DISPERSIONS

Note: this figure depicts dispersion across industries of average real *log*-wage, physical, ICT, intangible capital types and digital equipment per capita. Solid red and blue lines are related to wages and ICT capital, while dashed green, orange and purple lines are intangible capital, digital structures, and physical capital, respectively, all taken in per capita *log*-terms. Panel (a) plots the yearly difference between top and bottom 10% of each component, while Panel (b) plots the associated *log*-variance. Series are standardized and indexed to 1 in 1998, so that both y-axis indexes the respective measure given the initial value at unity. Plots are referred to 3-digit US 2017 NAICS industries. *Source*: BEA and own calculations.

servation:[21] abstracting from physical capital for the reasons so far, the variance of intangibles and digital structures is not able to path that of real wages if these two capital types are not combined into the unique ICT capital measure, as detected by Panel 1b. Relevant is the role played by the combination of intangible capital and digital equipment: together, these are able to better track the stream in the real wage variance; if taken alone, industry-level intangibles can roughly track wages around 2012, while digital equipment plays a role only from 2012 and beyond.

FACT 1 (Industry capital gaps) *Dispersion in physical capital-labour ratio is decreasing across industries, while it is not that of ICT capital-labour ratio.*

Further evidence on the importance of ICT capital on real wages is provided by Table A.1, where a set of Fixed-Effects (Fe) panel regressions confirms the above regularities. While a point increase in physical capital increases real wages, the point increase in per worker ICT capital is less significant (column 1): this lack may be interpreted as being driven by an heterogeneous effect across industries. Relevant is the role played by intangible capital, while less importance is owned by digital equipment: intangibles seem to control major variation in wages (column

[21] A growing empirical and methodological debate points to the importance of this complementarity. For example, Corrado et al. (2017) establish how returns to ICT crucially depend on "unmeasurable" intangibles, thus detecting an ICT-intangible capital complementarity in macro-level data both for US and EU. Complementarity argument in present also in Crouzet et al. (2022): since intangible capital lacks a physical presence, its functioning require a storage medium.

2); the interaction between intangibles and digital equipment (column 3), if further combined with all the other types of capital (column 4), is still significant to account for the variation in industry real log-wage.

1.2. Accounting for workforce composition

Production does not occur with capital only. A thorough examination of wage dispersion necessitates a careful consideration of the composition of the labour force within each industry. To this end, reference is made to the US Bureau of Labor Statistics' Occupational Employment and Wage Statistics (OEWS) programme, which provides comprehensive data covering over one hundred occupational categories. The final dataset employed in this analysis comprises information on 62 private-sector industries at the 3-digit US 2017 NAICS system over the period 2003–2022. This dataset forms the empirical foundation for the subsequent investigation.

Since their advent, advances in technical and technological processes have raise the issue of its underlying effects on employees' qualification requirements at both aggregate and industry layers (*e.g.*, Horowitz and Herrnstadt 1966, Rumberger 1981, Autor 2022), and that the mechanism through which these impact workers does not transmit uniquely on the absolute level of occupational employment, but especially in its relative term.[22] A natural intuition to analyse is whether changes in the relative workforce of each task are related to changes in the mass of employed workers hired by industries, or whether these shifts occurred due to movements in the labour tasks' composition within those industries, that is, how much of the change in the relative labour force of a task can be attributed to changing sizes of industries and how much it is due to changes in the reallocation of worker-types within those industries. Denoting the set of tasks as $\{a, a'\} \in \mathcal{A}$ and with $s \in \mathcal{S}$ that of industries, the following labour force decomposition provides the answer to this inquiry:

$$\Delta\left(\frac{\ell\,(a)}{\ell\,(a')}\right) = \underbrace{\sum_s \overline{\left(\frac{\ell\,(a,s)}{\ell(s)}\right)}\,\Delta\left(\frac{\ell\,(a,s)}{\ell\,(a',s)}\right)}_{\textit{within-industry: substitution effect}} + \underbrace{\sum_s \overline{\left(\frac{\ell\,(a,s)}{\ell\,(a',s)}\right)}\,\Delta\left(\frac{\ell\,(a,s)}{\ell(s)}\right)}_{\textit{between-industry: size effect}} \tag{1}$$

Shifts in the economy-wide ratio of task-s to task a' can be decomposed in *within*- and *between*-industry: the first component isolates movements in the task ratio $\left(\frac{\ell(a,s)}{\ell(a',s)}\right)$ keeping constant an expansion in the industry-specific task workforce relative to its total employment $\left(\frac{\ell(a,s)}{\ell(s)}\right)$, while the second term accounts for changes in the share of each task in the total industry labour force, absent any dynamics in the task ratio.[23] In other words, the *within* component reflects changes in the *task ratio*, namely the ratio of task-s to task a' in each industry (thus capturing the

[22] Refer to Melman (1951) and Braverman (1974) for an analysis over the period 1820-1970.

[23] Note that the changing components, $\Delta\,(x)$, reflect the fitted linear trend of x estimated from a panel Fixed Effects (Fe) regression with both year and industry fixed effects, the same regressions used to plot the aggregate dynamics of task-specific linear trends in Figure A.3.

TABLE 1: LABOUR FORCE COMPOSITION

	routine		non-routine	
interval	*within*	*between*	*within*	*between*
2003-2008	83%	17%	38%	62%
2009-2015	81%	19%	58%	42%
2016-2022	78%	22%	69%	31%

Quantification of eq. (1); *changing components* (Δ) *are linear trends predicted by a Fixed Effects (Fe) regression of the form* $(y_t \mid \mathcal{X}_t) = \beta_c + \beta_t \mathcal{X}_t + u_t$, *with* y *representing the task ratio, and* $\mathcal{X}$ *a vector of industry and year fixed effects, at 3-digit US 2017 NAICS industries. Source: BLS and own calculations.*

substitution and reallocation of tasks), while the *between* component reflects variations in the share of a given task relative to total occupied workers in the related industry (thus capturing the relative size of each task's workforce). Figure A.3 plots the dynamics in the fitted values of both routine and non-routine shares of industry-specific labour force computed from a Fixed Effects (Fe) regression with both year and industry fixed effects. As it appears, in the time window I am considering the presence of non-routine workers is increasing over time while occurring a routine share decline: this raises the question on the logic behind such structural change, that is whether the labour force composition of each industry is changing in size, or whether industries are more keen to employ non-routine workers at the expense of routine ones; this is exactly the point captured by eq. (1).

The output of the decomposition is reported in Table 1: upward movements in the task ratio of non-routine over routine workers over time occur within industries, meaning that the industry-fraction of non-routine workers is not increasing due to the expansion of the industry labour force, but rather to the replacement of routines with non-routines.[24] Opposite result is thus obtained for the task ratio of routine over non-routine workers: routine workers' share increases due to an expansion of the industry labour force, even if such change is contained (small increase) over time.

FACT 2 (Labour force composition) *Increases in non-routine relative share are determined by a substitution effect rather than by the employment size of industries.*

Finally, it is time to combine the results for capital types with that of labour force composition. The central idea to ratify is to check whether industries with major real wage growth are not only those increasing ICT capital but also those employing more non-routine workers. In fact, as in the model later on, non-routine workers are those whose work is more ICT-intensive compared to routine ones, who rather perform a manual job. Figure 2 confirms this suggestion: by grouping industries by

[24] A link between occupational distribution and industries is also present in Haltiwanger et al. (2024) since, due sorting effects, high (low) paying industries employ high (low) paying workers; however, the substitution argument across tasks is silent.

(A) Real wages vs. ICT capital ratio

(B) Real wages vs. task ratio

Figure 2: Industry Correlations

Note: each subplot of this figure represents the correlation of overall percentage change in industry-specific real log-wage per capita with both ICT capital ratio (ICT over non-ICT capital) in Panel (a), and task ratio (non-routine over routine workers) in Panel (b). The oblique (dashed-grey) line represents the fitting curve with its associated degree of correlation, while the horizontal (solid-black) line identifies the mean value of all industries' overall percentage change in real log-wage per capita. For a better graphical visualization, the ICT ratio takes constant the initial level of physical capital. Each circle is referred to a specific industry, and I report the label only for more and less virtuous (top and bottom 10%) industries; circles' size captures different groups of industries, each expressing the group's position in the distribution of overall percentage change in their real log-wage. Plots are referred to 3-digit US 2017 NAICS industries over the period 2003-2022. A further graphical representation can be found in Figures A.5a and A.5b. *Source*: BEA, BLS and own calculations.

their position in the real log-wage growth distribution, the correlation between the overall percentage change in real wages and the overall percentage change in both ICT ratio (ICT-to-physical capital) and task ratio (non-routine over routine workers) is significantly higher for top (in terms of highest real wage growth) than for bottom industries.[25] Even if such an approach is not aimed at detecting a causal relation among these values, I just point to the fact that industries having experienced highest percentage changes in real log-wages are those whose combination of factors of production has undergone, at the same time, a substantial rise in the share of both non-routine workers and ICT capital. Thus, it is not only a matter of isolated changes, but rather pivotal appears to be the interaction of these two ratios: in column 3 of Table A.2 the coefficient $\beta_{\Delta k \times \Delta \ell}$, considering the joint time changes in both ICT and task ratios, has a significant and massive effect on the change in real log-wages, and this effect is positively marked for industries at the top and bottom of the industry-wage growth distribution (Table A.3).

Further insights may be gained from Figure A.4; each line corresponds to the HP

[25] For a better graphical visualization, the ICT ratio considers the share of ICT capital relative to the initial share of physical capital for each industry to rule out the increase in physical capital (following Figure 1); when considering year-by-year ICT capital ratio, conclusions are unaffected.

filtered trend of the annual mean of each industry group in all the considered ratios. The pattern is the same shown so far: there is a clear-cut division across industries, where more virtuous ones – that have substantially raised their average real wage – are those which have increased both their ICT capital and non-routine workers shares, with a loured effect when moving downward the industry-wage growth distribution. An argument strongly reinforced by a bulk of quantile regressions, $\mathcal{Q}_\omega(log\,(w_t(s))\ \mid \mathcal{X}_{i,\omega t}, \mathcal{Z}_{j,\omega t}) = \beta_{i,\omega}\mathcal{X}_{i,\omega t} + \delta_{j,\omega}\mathcal{Z}_{j,\omega t} + u_{\omega t}$, where ω represents each quantile (defined on the independent variable), and $\mathcal{X}_i$ and $\mathcal{Z}_j$ are just controls. Regressions are either in log-levels and in log-standard deviation: positive impact of both task and ICT-to-physical capital ratios, with an increasing effect if one moves from the bottom to the top of the industry-wage distribution. These results are shown in Table A.4: the task ratio (β_ℓ) has a significantly greater impact on the increase in real log-wages compared to β_k, the ICT ratio (column 1). However, increases are not evenly distributed across industries: the effect of each ratio increases in magnitude along the distribution, with smaller impact for industries located far from the top (columns 2-5). It is worth to note how the interaction term has a massive magnitude only when considering the regressions in changes ($\beta_{\Delta k\times\Delta\ell}$) rather than in levels ($\beta_{k\times\ell}$), pointing to the conclusion that it helps addressing the over-time variation in real log-wages rather than their cross-sectional levels.

FACT 3 (Structural transformations) *Industries marked by highest changes in real wages experience a substantial rise in their non-routine workers relative share along an increasing ICT capital ratio dynamics.*

When jointly considered, the presented stylized facts so far reveal an important characteristic of the inter-industry wage structure in the US: the dispersed increase in industries' real average wage is jointly determined by an increased dispersion in technology' and such differences in technology reflect differences in the labour force composition of each industry, with an higher rate of substitution of routine with non-routine tasks in industries which experience a larger and substantial increase in the stock of ICT capital relative to the physical one. Reminiscent from the introduction, these facts are opened to two interpretations: wage inequality across industries could be the result of *(i)* a *quantity* effect, under different paths in factor of productions; or *(ii)* a *structural* effect, due to changes in technology parameters governing the relationship between capital and labour types. These general equilibrium issues will be addressed in the remainder of the paper through the lens of an estimated model.

1.3. Connection to the existing literature

Concluding the empirical exploration, this section reinforces the existing findings on the between-industry component of wage inequality in the US. First, I explore which are the industries that most contribute to its trend, to then decomposing the contribution of given industry-groups into several components (employment and wage changes both within and between different industry groups).

From Haltiwanger et al. (2024), the industry $s \in \mathcal{S}$ contribution to wage inequality can be decomposed as

$$\underbrace{\Delta\, var\Big(w(s)-\overline{w}\Big)}_{\substack{\textit{between-industry}\\ \textit{wage variance growth}}} = \sum_{s} \overbrace{\Delta \underbrace{\left(\frac{\ell(s)}{\ell}\right)}_{\substack{\textit{employment}\\ \textit{share}}} \underbrace{\Big(w(s)-\overline{w}\Big)^{2}}_{\substack{\textit{relative}\\ \textit{wage}}}}^{\substack{\textit{industry } s \textit{ contribution to}\\ \textit{between-industry wage variance}}} \tag{2}$$

in which the employment share component allows to give the proper weight to each industry. $w(s)$ is the average real *log*-wage of industry-s, and $\overline{w}$ the associated economy-wide period mean. Further, a shift-share analysis provides insights on industry factors accounting for such variance growth, thus detecting the relative importance of wage $(w(s))$ changes versus employment share $(\ell(s))$ changes:

$$\underbrace{\Delta\left(\frac{\ell(s)}{\ell}\right)\Big(w(s)-\overline{w}\Big)^{2}}_{\substack{\textit{industry } s \textit{ contribution to}\\ \textit{between-industry wage variance}}} = \underbrace{\overline{\Big(w(s)-\overline{w}\Big)^{2}}\,\Delta\left(\frac{\ell(s)}{\ell}\right)}_{\textit{shift share: employment}} + \underbrace{\overline{\left(\frac{\ell(s)}{\ell}\right)}\,\Delta\Big(w(s)-\overline{w}\Big)^{2}}_{\textit{shift share: wage}} \tag{3}$$

Output for these two decompositions is reported in Table 2. Even at 3-digit US 2017 NAICS level, a small fraction of industries is the major giver: 93% of total dispersion in wage inequality is determined by 15 out of 62 industries which account for almost 40% of total employment. Among these industries, only 3 account for more than a half of total trend in real *log*-wage variance, with 8% of total employment share. Industry-related contribution to wage variance growth can be further inspected by exploiting the results of the shift-share analysis, which provides information about the role of changes in wage and in employment shares. As already pointed out in Fact n. 2, the size of industries in terms of employed workers is not so relevant in determining the routine and non-routine job tasks combination; from Table 2, an expansion of the relative labour force of industries plays a little role on wage inequality, while it is the relative wage component that is most important: major contribution to wage variance growth is not due to variations in the employment size, but rather to changes of the industry wage relative to the mean wage.

Similar exercise can be performed by dividing industries in terms of changes in real *log*-wage (second part of Table 2 and Figure A.5c). Top and bottom 25% industries account for 88% of wage inequality, and own almost 60% of total employment. The relative wage component is significantly more important than the employment-size one: changes in the size of industry-level workforce account for a little effect on wage inequality, thus reconciling with Fact n. 2. Finally, it can be concluded that major contribution to US wage inequality is due to a small fraction of industries, whose position is polar in the distribution of total changes in industry real wages;[26] these

[26] Exploiting this result, I also decompose the pattern in wage inequality by dividing industries in different groups. In eq. (A.1), I borrow from Kleinmann (2023) a decomposition quantifying the contribution of those groups of industries to wage inequality. This can be divided into wage variance within the group of industries,

TABLE 2: CONTRIBUTION TO BETWEEN-INDUSTRY WAGE VARIANCE

			share		shift-share	
contribution	*industries*	*variance*		*employment*	*wage*	*employment*
> 5%	3	.26	54%	8%	90%	10%
1% to 5%	7	.14	29%	18%	76%	24%
.05% to 1%	6	.05	10%	13%	124%	-24%
-.05% to .05%	46	.03	7%	61%	·	
quantiles						
0-25	15	.24	50%	31%	91%	9%
25-50	16	.04	8%	28%	77%	23%
50-75	16	.02	4%	15%	·	
75-100	15	.18	38%	26%	98%	2%

Estimates are referred to eq. (2) for 3-digit US 2017 NAICS industries. The last two columns report a quantification of the components in eq. (3); not reported estimates '·' imply that the shift-share for employment is highly less than zero. Operator Δ in the equations is $x_t - x_{t-1}$, and not a percentage change. Industries are grouped according to their own contribution to between-industry wage inequality in the first part of the table while, in the second part, grouping follows the overall percentage change in real log-wage per capita of each industry. Source: BEA and own calculations.

results align with the empirical findings outlined in Haltiwanger et al. (2024).[27]

FACT 4 (Contribution) *A small subset of industries drives the rise in wage inequality; these are in the tails of the industry-level wage growth distribution.*

Taking stocks, a brief recap of the empirical results is in order. So far, I have shown that in US, over the period 2003-2022, *(i)* industries are divergent for ICT capital rather than for non-ICT one, and there exists a positive co-movement of industry's changes in ICT capital and in real wages; *(ii)* changes in the task ratio (non-routine over routine workers) are occurring within rather than between industries, and are not due to an expansion in industry-specific labour force; *(iii)* industries that have experienced highest changes in real wages are those in which major changes in both ICT capital and task ratios have occurred; and *(iv)* a small subset of industries contributes most to wage inequality. That said, these findings provide the motivating background to build a model with industry-specific capital-labour substitutability and heterogeneous labour force composition to account for trends in wage inequality in the United States.

total employment reallocation across groups, and co-movement of variance and employment shares. Table A.6 reports the estimates: industries in the tails of the wage growth distribution account for most of the *within-group* dimension in wage-inequality (almost 80%). Still, there is small room for employment share changes (even if more pronounced since measured in variance terms). An important observation to be made is that the *services sector* owns a substantial portion of US wage inequality, thus winking at the literature on the decline of the US manufacturing sector (*e.g.*, Moro 2012, Buera and Kaboski 2012, León-Ledesma and Moro 2020).

[27] According to the authors, from 1996 to 2018 the 10% of 4-digit US 2017 NAICS industries account for about 98% of the total increase in between-industry wage dispersion.

2. Model

To rationalize the presented empirical regularities, I build and simulate a structural general equilibrium model of structural transformations.[28] The households block features a skill-related heterogeneity: households are *ex-ante* divided in routine and non-routine workers, and each sorts into firms and industries given heterogeneous productivities.[29] Final and sectoral outputs are competitively aggregated, while firms in each industry compete monopolistically; they all use ICT and non-ICT capital types, where non-routine labour is complementary to ICT capital, while routine workers are substitutable. Hence, the structure of the economy identifies production functions to be analogous in all industries except for their degree of substitutability across factors of production. To better understand the role of substitution parameters, I do not consider productivity differences across industries.[30]

2.1. Households

There is a unit mass of households, each labelled as i, split in types $a \in \mathcal{A}$. Household i of type a gets utility from consumption, $\mathcal{C}_i$, and it is increasing in a known idiosyncratic factor, $\wp_h^i(a,s)$, drawn once from a specified distribution, measuring its efficiency level when working in firm $h \in [1, H]$ in industry $s \in [1, S]$,

$$\mathcal{U}_h^i(a,s) := log\ \mathcal{C}^i + \wp_h^i(a,s) \tag{4}$$

An household can invest either in bonds $\left(b^i\text{, which are in zero net supply}\right)$ at the rate r_t, and in capital types $\left(k^i(j), \forall j = \{phy, ict\}\right)$, while receiving dividends from firms $\left(\mathcal{D}^i\right)$, so that its expected utility problem displays the budget constraint to be

$$\begin{aligned}&\mathcal{C}_t^i + I_t^i(phy) + I_t^i(ict) + b_{t+1}^i - (1+r_t)b_t^i = \\ &\qquad w_{h,t}(a,s)\mathcal{B}_{h,t}(a,s)\ell_h^i(a,s) + R_t(phy)\,k_t^i(phy) + R_t(ict)\,k_t^i(ict) + \mathcal{D}_t^i\end{aligned}$$

where the wage rate associated to type-a in firm-industry pair (h,s) is $w_h(a,s)$, with labour $\ell_h^i(a,s)$ inelastically supplied and set to unity. The firm benefit of household type-a is defined to be $\mathcal{B}_{h,t}(a,s) = \left[g_{h,t}(a,s)\right]^{-\varsigma}$, where $g_{h,t}(a,s)$ reflects the relative share of that given task, negatively scaled by the elasticity parameter ς (an indicator of the degree of substitutability among job tasks); as a whole, these last three components identify household's earnings. Any capital stock depreciates at a rate δ and accumulates over time by a law of motion as a negative function of ζ_t^i (the relative ICT capital share) that scales new capital investment, $I_t^i(j)$, under the

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[28] Industry-heterogeneous trends in the elasticities of substitution between capital and worker categories.

[29] Due to the absence of a non-employment option and unemployment, the terms household(s) and worker(s) are then used interchangeably.

[30] Sectoral productivity and structural changes are theoretically analysed by Ngai and Pissarides (2007), linking the elasticity of substitution among intermediate inputs to the sectoral reallocation of employment. Moreover, in Section 5 I consider the effect of estimated industry-level productivity series on wage dispersion.

idea that as the stock of capital owned by household i becomes more sophisticated it is required an higher rate of capital investment to keep constant the future stock of the given capital type.[31] Inter-temporal utility maximization implies a standard Euler condition for future path of marginal utility from consumption, and an equation displaying the evolution of the capital rental rate

$$R_t = (1 + r_{t+1})\zeta_t - (1-\delta)\,\zeta_{t+1} \tag{5}$$

in which changes across states of R_t are determined by changes in the (aggregate) relative quantities across capital types, $\zeta_t = \int_i \zeta_t^i \,\mathrm{d}i$. In the spirit of Karabarbounis and Neiman (2014), eq. (5) determines that investing in capital types is profitable as long as the marginal benefit of investment is at least lower than its marginal cost.

In a market economy households do not randomly sort across firms: as noticed, every worker is assumed to have a known efficiency level for each possible combination of firm and industry layers. Dropping time-t subscript, the idiosyncratic *productivity* when working in firm (h, s) is drawn once by household i, type-a from a multivariate Frechét-type cumulative distribution

$$F_i\Big(\wp^i_{h,\ldots,H}(a,1),\ldots,\wp^i_{h,\ldots,H}(a,s),\ldots,\wp^i_{h,\ldots,H}(a,S)\Big) = exp\left[-\sum_s\left(\int_h \wp^i_h(a,s)\,\mathrm{d}h\right)^{-\theta}\right]$$

where its shape parameter, $\theta > 1$, is the degree of dispersion among different idiosyncratic productivities (*i.e.*, the labour supply elasticity),[32] and higher values of θ imply lower degrees of dispersion; without loss of generality, location and scale parameters are normalized to 1. Such Type-I Extreme Value Distribution identifies a discrete choice on how household of type-a sorts into firm (h, s) given heterogeneous productivity levels across different firm-industry pairs.[33] Central implication of this modelling choice is that workers may be employed in each firm in every industry, but each of them has heterogeneous productivity levels depending by the firm and the industry where employed. As a consequence, it can be stated that household i has an *absolute* advantage given by the chance of working in every firm and industry as type-a, but also a *comparative* advantage: among the same task group, workers will ended up in the firm-industry pair where they are more efficient (*i.e.*, in the job place

[31] Household i's capital dynamics follows a law of motion as $k^i_{t+1}(j) = \frac{I^i_t(j)}{\zeta^i_t} + (1-\delta_j)k^i_t(j)$, $\forall j = \{phy, ict\}$.

[32] It measures the centrality of a change in labour supply of task-a induced by a change in its firm-h, industry-s wage level. Rogerson (2024) stresses the importance of the (aggregate) labour supply elasticity in macroeconomics, pointing to both intensive (average hours worked) and extensive (employed people in the total population) margins. In my model only the latter margin (relative task-a share of total employment) is considered, since households are assumed to supply inelastically one unit of work (so that $\ell^i_h(a,s) = 1$), linking this elasticity to a certain degree of workers' concentration in the labour market; see Figure 3.

[33] Self-selection concept dates back to Roy (1951)'s verbal-model, whose scope is to describe how the subjective choice for a given occupation would affect the distribution of wages: it is not only a function of gaps in potential wages, but rather it includes also occupational sorting choices. Roy's idea has been substantially tested in the literature (right after Heckman and Sedlacek 1985 and Borjas 1987), and the macroeconomic implications of such microeconomics sorting choice have been firstly introduced by Hsieh et al. (2019).

where they can perform the task-a job content in which they are more inclined to work as); this is referred to as a *segregation* effect.

The distribution of households' productivities – and thus the self-decision around employment choices – is mostly related to the specification of the labour supply of households, which is as well function of the wage levels of each firm (h,s). Choosing this way of describing sorting preferences allows to derive analytical form for the measure of each worker-type in firms and industries given the respective wage level: in Appendix B I show that the labour supply curve of each (a,h,s) takes the form of

$$\ell_h(a,s) = \left(\frac{w_h(a,s)}{\mathcal{W}_{\mathcal{H}}(a,\mathcal{S})}\,\frac{\mathcal{B}_h(a,s)}{\mathcal{B}_{\mathcal{H}}(a,\mathcal{S})}\right)^{\theta} \tag{6}$$

with $\mathcal{W}_{\mathcal{H}}(a,\mathcal{S}) = \sum_{h,s} w_h(a,s)$ and $\mathcal{B}_{\mathcal{H}}(a,\mathcal{S}) = \sum_{h,s} \mathcal{B}_h(a,s)$. Firm-level labour supply is modelled such that it is almost entirely driven by not only the *absolute* wage level for worker a in firm (h,s), but also by how such wage compares to related wages of others (the *firm pay premia* effect). In addition, to attract more workers of the same type (the *sorting* effect) a firm within an industry has to pay higher wages.

Such labour supply allows to summarize the role of wage premium, sorting and segregation, all effects of pivotal importance in shaping wage inequality: Haltiwanger et al. (2024) provide insights on the role played by these factors by underlying how wage dispersion across industries is mostly due to combination of sorting (referred to as the covariance of industry wage premium and the segregation effect across industries) and its associated wage premium.[34] More, Card, Rothstein, et al. (2024a) find how the correlation between workers sorting across industries and the associated wage premium is high.[35] An important observation is that I manage to trace a connection between the allocation of workers across selected industries and labour market imperfections in the sense of "new classical monopsony" (Manning 2021), where the elasticity of households' labour supplies is not fully flexible, but rather influenced by the variability in the household-specific productivities (θ).[36] Even if I will not allow firms to take their respective labour supply of each task-a as given (not encompassing a proper monopsony power), the equilibrium wage level of firm (h,s) directly determines the number and the type of workers working there through sorting and segregation effects. In other words, the constitutive assumptions of the model directly enhance a mechanism on the critical interaction of the

[34] Bringing forward the words of the authors, "high-wage workers are increasingly sorted to high-wage industries with rising industry premia and are increasingly working with each other" (Haltiwanger et al. 2024). In continuity with the work of Card, Heining, et al. (2013) for Germany, several empirical works (*e.g.*, Card, Cardoso, and Kline (2016) for Portugal, Alvarez et al. (2018) for Brazil, Barth et al. (2016), Song et al. (2019) and Haltiwanger et al. (2023) for US, Håkanson et al. (2020) for Sweden, Briskar et al. (2022) for Italy) detect how these major effects are increasingly impacting the distribution of wages.

[35] Using a cross-sectional approach at sectoral level, Gibbons, Katz, et al. (2005) show how the high-skill occupational sorting is determined by differentials in return to skills, and the comparative advantage motive, rather than learning, seems to affect the resulting wage premiums.

[36] In this perspective monopsony is not a dynamic search-and-matching friction; rather, its static nature ensures the labour supply elasticity a notable role, affecting labour in a fully competitive labour market.

workplaces' labour force composition with sorting and segregation effects, both associated to the firm-industry wage premium arising from not perfectly elastic labour supplies designed in a perfectly competitive labour market.

Remark 1 (Labour market elasticity, sorting and segregation) *Selected specification of households' productivities allows to characterize firms and industries workforce composition of tasks as determined by a not fully elastic labour supply elasticity interacting with equilibrium wage premium designed through perfect competition in the labour market.*

In fact, as from eq. (6), the number of workers of a given task-a willing to be employed in a certain firm-industry pair is determined by different optimal wage levels by firms in industries (wage premium), jointly with workforce composition in terms of both the firm-specific relative amount of workers of a certain type (sorting) and workers having the same efficiency in conducting that job task content (segregation). In this sense, workers in the same task are "highly rival factors" (Hicks 1932) since they can be freely substituted for one another, and this possibility ensures that high-wage workers do sort in high-wage firms and industries, and also that more efficient people would be preferred to get a job in high-wage workplaces than ones who are less productive. Such idea can be formalized using an Horvath (2000)'s aggregator: the aggregate type-a workforce of industry-s can be taught as a CES aggregator of firm-specific labour measures of eq. (6), taking the form

$$\ell(a,s) = \left[\int_h \left(\ell_h(a,s) \right)^{\frac{1+\psi}{\psi}} \mathrm{d}h \right]^{\frac{\psi}{1+\psi}} \tag{7}$$

since each worker i is endowed with $\ell_h^i(a,s) = 1$ unit inelastically supplied. Here, as $\psi \to \infty$, type-a workers become perfect substitutes; conversely, for any given value of parameter ψ comprised in $[0, \infty)$ workers won't be freely substituted across firms in the same industry. As a natural consequence, each worker would work in the firm (h,s) paying the highest wage according to its $\wp^h(a,s)$. More, at the intensive margin, firms in the same industry would pay the same wage level.[37]

Assumption 1 *Since households' productivities are Frechét-distributed, workers are perfectly mobile across firms within an industry, and immobile across industries.*

Parameter θ identifies the labour supply elasticity and, since the major determinant of the labour supply is the wage level offered by firms in each industry, it can be further interpreted as a measure of labour market concentration arising from the distribution of households' productivities (sorting and segregation factors): as productivities become more dispersed, labour market polarization would reduce

[37] Crucial aspect to consider when moving from firm to industry dimension: free labour mobility within an industry − materialized when $\psi = \infty$ − allows to impose firms' optimal wages to be even, so to have a unique industry-s wage in equilibrium; see Proposition 1 and Remark 2.

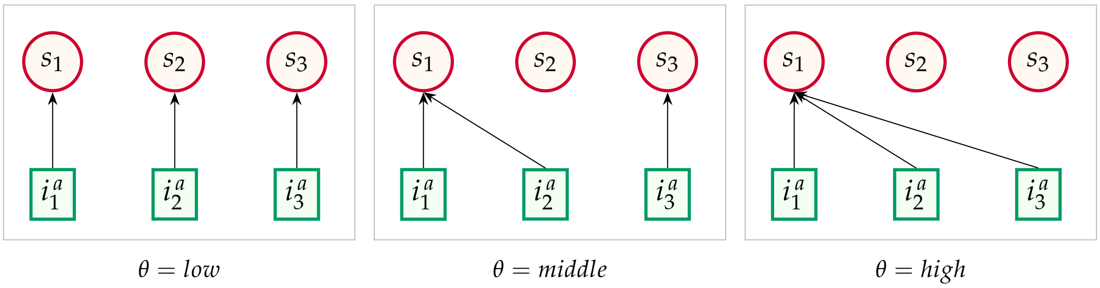

FIGURE 3: PRODUCTIVITY DISPERSION, SORTING AND SEGREGATION

Note: this graph displays a stylized example on how productivity dispersion of households relates to labour market concentration at industry level. Each i^a represents an household of task-a, while s is a specific industry. The higher is the value of θ, the lower is the dispersion of households' productivities, so that the larger are the effects of sorting and segregation, thus the higher is the degree of labour market concentration of workers across industries.

due to a reduction in the power of sorting/segregation effects. A better conceptualization of the relation between the variability of productivity distribution and employment choices is sketched in Figure 3. To explore the mechanism behind θ, consider a stylized economy in which there are just $\{s_1, s_2, s_3\} \in \mathcal{S}$ industries comprising just one (representative) firm, and only three households of unique type a. Households' productivities across given industries may acquire only three values, $\wp^i(a,s) = \{low, middle, high\}$ depending where employed with parameter θ determining common dispersion: when $\theta = low$, there is high variability in efficiency levels, meaning that all households' productivities are highly dispersed in the sense that each household picks a different industry, thus determining a low polarization in the labour market; the opposite occurs in the case when $\theta = high$: efficiency levels result to be very clustered, so that households do sort in the same industry reflecting substantial labour market concentration, while an intermediate case occurs when $\theta = middle$. In a general perspective, I am proxying the degree of type-a workers' concentration at industry level to be directly proportional to the degree of variability in households' productivities (and therefore to the labour supply elasticity).

2.2. INDUSTRIES

The supply side is made of a countable set of industries $s \in \mathcal{S}$, each producing a specific variety $y(s)$. A perfectly competitive final good producer combines intermediate outputs from industries using a Constant Elasticity of Substitution (CES) technology

$$Y = \left(\sum_s y(s)^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}}$$

where $\eta > 1$ is the elasticity of substitution among varieties of differentiated goods/services from industries. Final producer's optimizing behaviour gives birth to a relative demand of each industry-s output, given by $\frac{y(s)}{Y} = \left(\frac{p(s)}{P}\right)^{-\eta}$, with aggregate price index $P = \left(\sum_s p(s)^{1-\eta}\right)^{\frac{1}{1-\eta}} = 1$ since final good is competitively supplied.

A unitary mass of monopolistically competitive homogeneous firms, indexed with $h \in \mathcal{H}$, is comprised in all industries. Given market power of firms, aggregation for industry-s bundles together different varieties by a new CES aggregating function

$$y(s) = \left(\int_0^1 y_h(s)^{\frac{\epsilon-1}{\epsilon}}\, \mathrm{d}h\right)^{\frac{\epsilon}{\epsilon-1}}$$

where $\epsilon > 1$ is the sectoral elasticity of substitution among firms' varieties. In a way analogous to final producer, the conditional demand of firm (h,s) arises from competitive profit maximization at industry level:

$$y_h(s) = \left(\frac{p_h(s)}{p(s)}\right)^{-\epsilon} y(s) \tag{8}$$

with the sectoral price index being $p(s) = \left(\int_0^1 p_h(s)^{1-\epsilon}\, \mathrm{d}h\right)^{\frac{1}{1-\epsilon}} = 1$.

Firm-h in industry-s comprises two types of households, $a = \{rt, nrt\}$: non-routine (nrt) workers are complementary to ICT capital, while routine (rt) labour force is substitutable with the ICT composite good produced under the non-routine-ICT capital complementarity. The production function $y = f\left(k^{phy}, k^{ict}, \ell^{rt}, \ell^{nrt}\right)$ of firm (h,s) exploits that in Krusell et al. (2000), that is

$$\begin{gathered} y_h(s) = \left(k_h(phy,s)\right)^{\alpha}\left[\mu\left(\ell_h(rt,s)\right)^{\varsigma} + (1-\mu)\left(q_h(s)\right)^{\varsigma}\right]^{\frac{1-\alpha}{\varsigma}} \\ \text{with} \\ q_h(s) = \left[\lambda\left(k_h(ict,s)\right)^{\varrho} + (1-\lambda)\left(\ell_h(nrt,s)\right)^{\varrho}\right]^{\frac{1}{\varrho}} \end{gathered} \tag{9}$$

where $k_h(phy,s)$ and $k_h(ict,s)$ are non-ICT and ICT capital, $\ell_h(rt,s)$ and $\ell_h(nrt,s)$ are measures of routine and non-routine workers, while μ and λ are just weighting parameters that govern output share of each firm (h,s); parameter α is the physical capital share of output. Elasticity indicators (ϱ, ς) are $\varrho = \frac{\rho-1}{\rho}$ and $\varsigma = \frac{\sigma-1}{\sigma}$.

ASSUMPTION 2 *Substitution elasticities $\rho_s, \sigma_s \in [0, \infty)$, physical capital and distributive shares $\alpha_s, \mu_s, \lambda_s \in (0,1)$ are sector-specific. Since elasticities are finite, each industry adopts strictly positive levels for capital and labour quantities.*

Parameters are all industry specific and will be *ad-hoc* calibrated. In particular, ρ is the elasticity of substitution between *ICT capital* and *non-routine* labour input (*i.e.*, the CES composite), while σ identifies the elasticity of substitution between *routine* labour input and the *CES composite*. The CES structure imposed above yields a symmetry constraint in the interpretation of σ: it is implied that the elasticity of substitution between routine and non-routine workers is the same as that between routine labour force and the ICT composite (see Krusell et al. 2000), and I will refer to them interchangeably. Capital-task complementarity requires that $\sigma > \rho$: this condition resorts the idea that technological process (namely an increase in ICT capital relative to non-ICT one) widens the relative demand of non-routine labour force, thus lessening that of routine workers.

Given the market structure, the formation of wages is decided at firm level considering monopolistic competition among firms in the same industry. Profit maximizing behaviour thus implies the Cobb Douglas-nested CES production function in eq. (9) to be subject on the conditional firm demand in eq. (8):

$$\max_{p_h(s),k_h(j,s),\ell_h(a,s)} \left[\mathcal{D}_h(s) \mid y_h(s)\right]$$

with $\mathcal{D}_h(s)$ being the profits of firm-h in industry-s. Within and industry, firms are all homogeneous; thus, any wage decision by firm (h,s) is not going to alter the sectoral wage level.[38]

Assumption 3 *Firms are atomistic, so that any wage level offered by a firm* (h,s) *only does not affect the sectoral one:* $\frac{\partial w(a,s)}{\partial w_h(a,s)} = 0 \; \forall a,h,s.$

Under this assumption, equilibrium wages paid by firm (h,s) are set, for routine and non-routine workers, respectively, to

$$\begin{aligned} w(rt,s) &= \left[\Lambda(s)\,\chi(rt,s)\,\Big(k(phy,s)\Big)^{\alpha}\,\mathcal{V}^{\frac{1-\alpha-\varsigma}{\varsigma}}\,\left(\frac{\mathcal{B}(rt,s)}{\mathcal{WB}(rt,\mathcal{S})}\right)^{\theta(\varsigma-1)}\right]^{\frac{1}{1+\theta-\theta\varsigma}} \\ w(nrt,s) &= \left[\Lambda(s)\,\chi(nrt,s)\,\Big(k(phy,s)\Big)^{\alpha}\,\mathcal{V}^{\frac{1-\alpha-\varsigma}{\varsigma}}\,\mathcal{Q}^{\frac{\varsigma-\varrho}{\varrho}}\,\left(\frac{\mathcal{B}(nrt,s)}{\mathcal{WB}(nrt,\mathcal{S})}\right)^{\theta(\varrho-1)}\right]^{\frac{1}{1+\theta-\theta\varrho}} \end{aligned} \tag{10}$$

where industry-specific composite parameters are given by $\chi(rt,s) = (1-\alpha)\mu$ and $\chi(nrt,s) = (1-\alpha)(1-\mu)(1-\lambda)$, while $\Lambda(s) = p(s)\,\mathcal{M}^{-1}$ is an indicator combining the industry-specific price level multiplied by the price mark-up, $\mathcal{M} = \frac{\epsilon}{\epsilon-1}$, and the aggregate element $\mathcal{WB}(a,\mathcal{S}) = \sum_s \mathcal{W}_{\mathcal{H}}(a,s)\mathcal{B}_{\mathcal{H}}(a,s)$; see Appendix B for the definition of the other components. Aggregate industry wage is thus found by averaged aggregation among job tasks: $w(s) = (\mathcal{A})^{-1}\sum_a w(a,s)$.[39]

Proposition 1 (Firm and industry layers) *In an economy characterized by sorting and segregtion effects and a not perfectly elastic labour supply where the measure of workers in a given firm is determined by its wage relative to the others, as long as*

(a) firms within an industry have the same size; or

[38] This assumption is particularly important in the proof of Proposition 1.

[39] Following eq. (7), worker-a wage is given by $w(a,s) = \left[\int_h \Big(w_h(a,s)\Big)^{\frac{1+\psi}{\psi}} \mathrm{d}h\right]^{\frac{\psi}{1+\psi}}$ with $\psi = \infty$.

(b) *workers are perfectly mobile across firms within an industry,*

$$\frac{\partial \ell_h(a,s)}{\partial w_h(a,s)} = -\frac{\partial \ell_{h'}(a,s)}{\partial w_h(a,s)} \quad and \quad \frac{\partial w_h(a,s)}{\partial \ell_h(a,s)} = \frac{\partial w_{h'}(a,s)}{\partial \ell_{h'}(a,s)} \quad ,$$

profit-maximizing wages set by firms in a specific industry are equal, and thus the unique optimal wage level can be directly written under industry notation. Moreover,

(c) *workers are immobile across firms between industries.*

Proof in Appendix B.

Besides formal proofs, the movement of workers across firms and industries is directly influenced by the assumed distribution of households' idiosyncratic productivity parameter $\wp_h^i(a,s)$. In fact, it could be not necessary to impose whether workers' movements are free or not, since the *max-stability property* of the Frechét distribution ensures that a worker, once choosing a workplace, will not move nor across firms neither among industries: since households' productivities are so distributed, such property guarantees that its maximum is as well distributed (from Mc Fadden 1974). As a result, each household always picks its utility-maximizer productivity level $\left(\wp_h^i(a,s)_{max}\right)$. Note that the imposed within-industry firm-homogeneity implies that each worker performs its job task content with the same productivity among firms in the same industry, *i.e.*, $\wp_h^i(a,s) \equiv \wp_{h'}^i(a,s)$ with $h' = \{1,\ldots,H\} \in s$.

Remark 2 (Max stability and workers' movement) *As from eq. (4), a worker has no incentive to choose a workplace where performing worse since*

$$\mathcal{U}_h^i(a,s) \mid \wp_h^i(a,s)_{max} \; > \; \mathcal{U}_h^i(a,s) \mid \forall\, \wp_h^i(a,s) \in \left[\wp_h^i(a,s)_{min}\,,\, \wp_h^i(a,s)_{max}\right)$$

is ensured by each worker's selection of its maximal productivity for the (h,s) tuple. In addition, since firms are symmetric within an industry, the sorting choice is uniquely driven by the dispersion of households' productivities between industries so that workers are free to move across firms within an industry while getting the same utility.

Interpreting eq. (10), both wages are increasing in non-ICT capital and with the price level, and each wage level considers the economy-wide wage of each task. Due to the imposed production structure, the wage series for non-routine workers is directly affected by the evolution in the ICT composite, namely the joint evolution of ICT capital and non-routine workers, while that of routine workers does not. In addition, differences among tasks are also reflected in the unlike importance of the two elasticities of substitution, ρ and σ: while routine workers are first-order impacted by the elasticity of substitution among themselves and non-routine workers, the latter group is majorly affected by the elasticity parameter proper of the ICT composite, namely the elasticity of substitution between ICT capital and non-routine workers. It should be further noticed that the two elasticities have second-order impact on wages due to their presence in total industry output $(\mathcal{V})$. Consistently, an increase in the industry benefit of a job task, due to a substitution effect (ς) following an increase in the relative share of the other task, drives up wages: for example, since optimal conditions refer to average wage of routine (non-routine) task, an increase in $\mathcal{B}(rt, s)$ implies that there are more non-routine relative to the number of routine workers, thus driving up (down) the average wage of routines (non-routine) workers. Moreover, both wages are not decreasing in their aggregate task wage in $\mathcal{W}(a, \mathcal{S})$, but rather increasing if $(\varrho, \varsigma) < 1$ holds, as from a later estimation in Section 3.2.[40]

Cross-sectional differences in ρ and σ do not reflect only divergences for comparable tasks, but especially across industries. Under no differences, if the industry-level distribution of capital and worker types is the same, then wage premiums would have been identical. What I am uttering here is that industries' characteristics related to the way in which these are organizing their own production plans are central to explain real wage differentials, whose divergence is mainly determined by different degrees of complementarity/substitutability among factors of production. These two parameters will be *ad-hoc* calibrated later on, thus reflecting *structural differences* among industries. Moreover, elasticities are not the only industry-specific parameters: there is also the block of "share" parameters comprised in $\chi(a, s)$, $\forall a, s$. These are the physical capital as a share of output (α), and the weights associated to both routine workers (μ) and ICT capital stock (λ) in the production of industry output $y\,(s)$. Note how such parameters, as the pair (ρ, σ), do not reflect cross-sectional differences among tasks (they are the same within industries) but only that across industries, meaning that the model is particularly suited to study inter-industry wage differentials, and not those across tasks.

Finally, parameter θ is common to all industries since it reflects the strength of sorting and segregation effects thus proxying the economy-wide level of labour market concentration (as in Figure 3). The underlying idea beyond is that of a single distortion in the labour market: as sorting and segregation effects become stronger the workforce composition of each industry is less diversified, and the economy would experience a structural movement of given tasks towards selected industries.

Capital choices. Closing the model, profit maximization by firm-h in industry-s not only displays the optimal amounts of each type-a's wage rates, but also a choice on the optimal quantities of both ICT and non-ICT capital stocks:

$$\begin{aligned} k_h\,(phy, s) &: \; p_h(s) f_{k_h(phy,s)} = \mathcal{M}R(phy) \\ k_h\,(ict, s) &: \; p_h(s) f_{k_h(ict,s)} = \mathcal{M}R(ict) \end{aligned} \tag{11}$$

where $\mathcal{M} = \frac{\epsilon}{\epsilon - 1}$ is the (constant) price mark-up, $f_{k_h(j,s)}$ being marginal products of both capital types from the production function specified in eq. (9), and $R\,(j)$ the capital-specific rental rate, for $j = \{phy, ict\}$. Note that these conditions are pivotal to determine how to estimate the elasticity combination (ρ, σ) as from eqs. (12)-(13).

[40] In this case there would be that $\left[\sum_s \mathcal{W}_{\mathcal{H}}(a, s)\right]^{-\theta([\varrho,\varsigma]-1)}$ with $-\theta(\,[\varrho, \varsigma] - 1) > 0$.

According to the structure of the model, equilibrium conditions read as follows.

(Equilibrium) *An equilibrium for this economy is defined as an households' choice of job place, a combination of factors' prices* $\big(w(a,s), R(phy), R(ict)\big)$*, and a set of aggregate quantities* $\Omega = \big\{Y, K(phy), K(ict), L(rt), L(nrt)\big\}$*, such that*

(a) Each household picks the firm-industry tuple that maximizes eq. (4);

(b) According to the occupational choice, each household maximizes its expected-utility version of the utility in eq. (4);

(c) Final and sectoral good producers maximize their revenues;

(d) Given the availability of workers in each job task as in eq. (6), optimal wages are determined by the equilibrium of labour demand and supply;

(e) Firms choose also capital bundles to maximize their profits;

(f) All markets clear, shaping Ω*.*

Proof in Appendix B.

3. From theory to data

In this section I quantitatively evaluate the model and bring it to the data. To gauge the performance and the consistency of the model in addressing salient features of the inter-industry wage structure of the United States economy, I split the universe of industries into three groups (following the "contribution" result – Fact n. 4 – of the data motivating section), namely the top 25%, the middle 50% and the bottom 25% of industries according to the overall growth in their real log-wage. The time window considered is the usual, spanning from 2003 to 2022.

3.1. Validating the model implications

As a first step to validation, I turn to analyse two main implications arising in the model; the following results should be interpreted as pure correlation.

Wage equation. I start by quantifying the relevance of the labour force composition on the industry-specific wage level. In fact, beside the usual role of capital and labour types in both $\mathcal{V}$ and $\mathcal{Q}$, the resulting industry-specific wage level arising by the aggregation wage specifications in eq. (10) considers a sizeable role of the industry benefit of each task, namely $\mathcal{B}(a,s)\ \forall s$, which points directly to the substitution among job tasks at the industry layer. To give a sense of this factor, I am going to quantify its effect by providing reduced-form evidence on how it impacts on the industry wage. In this respect, a set of regressions

$$\Big(log\big(w_t(s)\big) \mid \mathcal{X}_{i,t}, \mathcal{Z}_{j,t}\Big) = \beta_c + \beta_i \mathcal{X}_{i,t} + \delta_{j,t}\mathcal{Z}_{j,t} + u_t$$

where $\mathcal{X}_i$ comprises the regressors (task ratio and its inverse) and $\mathcal{Z}_j$ is a set of employment related controls, is performed. Results are presented in Table 3, in

TABLE 3: INDUSTRY WAGE AND RELATIVE TASK SIZE

	$log(w(s))$		
	(1)	(2)	(3)
$\ell(rt/nrt)$	.016*** (.006)	.001 (.007)	-.020*** (.002)
$\ell(nrt/rt)$	.129*** (.036)	.250*** (.084)	.318*** (.043)
Industry FE	✓	✓	✗
Time FE	✗	✓	✗

*Significance level at * (p<0.05), ** (p<0.01), *** (p<0.001). Standard error in parentheses. Analysis at 3-digit US 2017 NAICS industries in 2003-2022 on* $N = 1240$ *observations. The Fixed Effects (Fe) regressions are of the form* $y\left(log\left(w_t(s)\right) \mid \mathcal{X}_{i,t}, \mathcal{Z}_{j,t}\right) = \beta_c + \beta_i \mathcal{X}_{i,t} + \delta_j \mathcal{Z}_{j,t} + u_t$, *with* $\mathcal{X}_i$ *being the regressors, and* $\mathcal{Z}_j$ *a set of controls. All series are in logs. Constant not reported to save space.* Source: *BEA, BLS and own calculations.*

which each column identifies a different specification. Column 1 reports the baseline estimation, with industry Fixed Effects (Fe) only: a positive effect of increasing both ratios is detected, with the ratio of non-routine over routine workers having a stronger impact on industry real *log*-wage; this confirms either stylized Fact n. 3 and the theoretical wage setting equations. More, the role of industry-related characteristics is in column 3, where I address cross-sectional results by avoiding to consider Fe across industries: in this setup, increasing the share of routine in non-routine workers would decrease wages, thus contrasting with the industry-level aggregated version of eq. (10). The direction of the impact of relative non-routine tasks ratio remains unchanged but sizeable compared to the baseline specification.

Employment and relative wages. Another central hypothesis of the model arises from the labour market since the measure of task-a in industry-s takes the form of eq. (6), those linking task-employment levels to relative nominal task-wages. Regression procedure involves the same computations as in the case of the wage equation, and results are shown in Table C.1. The model well suits with the empirical relation, since both employment measures increase with the associated relative wage level. Sizeable effect is for routine workers, and even more for non-routine workers, meaning that as an industry increases its wage of a given task relative to the rest of the economy, then employed workers in that task increase as well.

Having in mind the role of labour force composition on industry wages, and the interconnection between the considered task measure and its relative wage, the main model's implications are empirically corroborated. Next, I calibrate and validate the model's ability to address the main features of the US inter-industry wage structure.

3.2. CALIBRATION

The vector of structural parameters to be calibrated is $\Theta = \left(\alpha_s, \epsilon, \lambda_s, \mu_s, \theta, \rho_s, \sigma_s\right)_{\forall s}$, and comprises features of both households and industries. A total of 17 parameters has to be computed; the strategy to estimate their values can be summarized in

Table 4: Summary of calibration

	parameter	*value* bottom	middle	top	global	**source**
α	*physical capital, share of $y(s)$*	0.263	0.195	0.514		*data*
ϵ	*demand elasticity across firms*				6	*external*
μ	*weight of routine workers in $y(s)$*	0.676	0.495	0.337		*MSM*
λ	*ICT capital share in $Q(s)$*	0.457	0.465	0.451		*MSM*
θ	*households' productivities dispersion*				11.3	*MSM*
ρ	*EoS, ICT capital and non-routine*	0.329	0.420	0.249		*estimation*
σ	*EoS, routine and ICT composite*	0.634	0.400	0.766		*estimation*

Set of estimated parameters of the model. "data" implies that the values are directly computed from data sources, while in "external" I choose standard calibrated values from the literature. "MSM" refers to the Methods of Simulated Moments as in Mc Fadden (1989). "estimation" refers to previously estimated values under a specific procedure; these values are taken from Table 5.

three steps: *(i)* some parameters are calibrated directly from the data, and some are externally taken; *(ii)* the elasticities of substitution are directly estimated following the procedure in Karabarbounis and Neiman (2014) via panel robust regressions; finally, *(iii)* most of the parameters are internally estimated by moment-matching of key features of the US economy. A summary of the calibrating procedure can be found in Table 4, where I report values either for each group of industries, and for common economy-wide parameters, and the types of estimation performed.

Data and external calibration. The elasticity of substitution among different varieties (ϵ) is externally set to 6 (so to have an annual mark-up of 20%). Differently, the production functions' share of non-ICT capital (α) are directly taken by manipulating data from BEA: as in Arvai and Mann (2022), I compute one minus the share of labour of total output, adjusted by considering the weight of non-ICT capital in the total capital stock of each group of industries. This procedure reports $\alpha = \{0.263, 0.195, 0.514\}$, order from bottom to top groups.[41]

Elasticities of substitution. The key model parameters, namely $(\rho_s, \sigma_s)_{\forall s}$, are estimated through the general equilibrium dimension of the model using the procedure outlined in Karabarbounis and Neiman (2014). For each industry-group, by defining the labour, capital and profits all in terms of income shares of total output, to then blending them with the F.O.C.s from the industry side – eq. (11), aggregated across firms and industries – to exploit the evolution of the capital rental rate in eq. (5), I am able to express the resulting equation in differences across two given periods. Taking a linear approximation around zero over-time trend, two separated

[41] Estimates are consistent with the argument against the usual "alpha equal one-third" rule – that the elasticity of output with respect to capital (*i.e.*, the capital share of output in a neoclassical production function) is 0.33 – by Vollrath (2024) for the US economy in 1948-2018.

procedures end up with two estimating equations that both relate the industry-level labour share $s_\ell(s)$ of a specific task with the relative quantity of ICT capital:[42]

$$\frac{s_{\ell,t}(nrt,s)}{1-s_{\ell,t}(nrt,s)}\widehat{s}_\ell(nrt,s) = \beta_c + (\rho-1)\,\widehat{\zeta}\,(s) + u_t \tag{12}$$

and

$$\frac{s_{\ell,t}(s)}{1-s_{\ell,t}(s)}\widehat{s}_\ell(s) = \beta_c + (\sigma-1)\,\widehat{\zeta}\,(s) + \beta_k\left(\widehat{\frac{\ell(nrt,s)}{k(ict,s)}}\right) + u_t \tag{13}$$

where hatted variables identify their own percent change between arbitrary t and $t+1$ periods, and ζ is the industry-related quantity of ICT capital relative to physical capital. The first equation allows to estimate the elasticity of substitution between ICT capital and non-routine workers (ρ), and it is derived by treating the ICT composite as a nested intermediate output.[43] Differently, eq. (13) estimates the elasticity of substitution between routine and non-routine workers (σ); such equation is derived from the full specification of the production function in eq. (9). Note that my estimates of the above regressions are not $\beta_\zeta^{(\rho,\sigma)} = \big([\rho,\sigma]-1\big)$, but rather directly the pair (ρ,σ) since the output variable on the left-hand side (labour share trend) is augmented with the trend in the relative stock of ICT capital, $\widehat{\zeta}\,(s)$.

The idea behind the two equations is straightforward. A negative relationship between trends in the labour share and trends in the relative quantities of capital occurs only when the two estimated elasticities report a certain complementarity degree, $(\rho,\sigma)<1$: taking out other possible economic factors (such as output productivity, capital-or labour-augmenting technology, profit share's or mark-up's growth), an increase in the relative quantity of ICT capital determines a consequential drop in the labour share of each occupation profile.[44] A graphical visualization of this negative relationship is in Figure C.1, where each panel plots the estimated left- and right-hand sides of eqs. (12)-(13), respectively: for both estimated elasticities, industries experiencing major increases in ICT capital stock relative to the non-ICT one are also those industries experiencing larger drops in both measures of labour share. The estimated overall correlations between trends in both labour shares and relative ICT stock among 3-digit US 2017 NAICS industries are $corr_\rho$ = -0.76 and $corr_\sigma$ = -0.75 between years 2003 and 2022.

Since I am considering a relative small time window, the estimation may suffer

[42] In Appendix C I sketch the solution to get the two estimating equations; see Karabarbounis and Neiman (2014) for further details. Note how these equations can be recovered from the general equilibrium properties arising in the fully specified model.

[43] In this specification, "output" is only determined by $q_h(s) = \left[\lambda\Big(k_h(ict,s)\Big)^{\varrho} + (1-\lambda)\Big(\ell_h(nrt,s)\Big)^{\varrho}\right]^{\frac{1}{\varrho}}$.

[44] The framework is reversed compared to that in Karabarbounis and Neiman (ibid.), where they need the elasticities to be greater than one, so that a drop in the user-cost of capital induced by a fall in the relative price of investment would determined a drop in the labour share due to a substitution effect between capital and labour which drives down the labour force as a share of total output. I decide to use quantities instead of prices since these can be directly observed industry by industry in the BEA tables.

TABLE 5: BASELINE ESTIMATION

	β^{ρ}_{ζ}	*Std.Err.*	*95% CI*	β^{σ}_{ζ}	*Std.Err.*	*95% CI*
bottom	.329	.04	$[.250, .407]$	.634	.08	$[.482, .785]$
middle	.420	.02	$[.375, .466]$	.400	.05	$[.310, .491]$
top	.249	.03	$[.188, .310]$	.766	.06	$[.656, .877]$

Estimation of the elasticities of substitution as given in eqs. (12) *and* (13)*, for 3-digit US 2017 NAICS industries over the period 2003-2022.* $\widehat{\rho}$ *refers to the estimate of the pair* $(\ell(nrt,s)\,;\,k(ict,s))$*, and it exploits the degree of substitutability between non-routine workers and ICT capital;* $\widehat{\sigma}$ *relates to the pair* $(\ell(rt,s)\,;\,[\ell(nrt,s),\,k(ict,s)]\,)$*, and it is the degree of substitutability between routine workers and the joint combination of non-routine workers and ICT capital.*

of potential outliers; a *robust* regression is performed in order to assign less weight (after some numbers of iterations) to data points which lie away from the regression line.[45] The resulting estimates of eqs. (12) and (13) are reported in Table 5. First thing to note is that each group of industries but the middle one is characterized by ICT capital-non routine tasks complementarity since it holds that $\sigma_s > \rho_s$ for any $s = \{bot, top\}$, reflecting an even adoption of technological change and thus an even effect on the composition of labour force across industries, but with an uneven impact since the (ρ, σ) differential has different magnitude across groups of industries. Consistent with Section 1, top industries exploit, more than the other industry groups, the reallocation of tasks in their industrial composition due to changes in technology. I now interpret the estimated values, which are all statistically significant.[46]

Start from ρ: top industries are those which have strongest ICT capital-non-routine workers complementarity, followed by bottom and middle industries, since $\rho \approx 1$ points for major "gross substitutability". This implies that top industries are maintaining more non-routine workers alongside to a marked stock of their ICT capital compared to the other groups of industries. Moving to the elasticity of substitution between routine workers and ICT composite good (or, due to symmetry, between routine and non-routine tasks), σ, a value closer to 1 implies that industries are less keen to keep their actual number of routine workers when the stock of ICT capital, together with their number of non-routine workers, increase. This is what Table 5 reports: top industries have lower propensity to employ routine workers at an equal

[45] As done by Karabarbounis and Neiman (2014): to overcome the impact of possible violations in Ordinary Least Squares (OLS) assumptions on the estimates due to few observations, this methodology downgrades the importance of outliers (characterized by larger residuals) so that the weight of each observation is no longer $\frac{1}{n}$ in a data sample with n observations. At each iteration, robust regression process drops observation whose Cook's distance is larger than 1 (high leverage points).

[46] Measuring the elasticity of substitution between capital and labour is challenging since it is due to both demand or supply factors. Yet, there is no a general consensus on its exact value. Available – either aggregate or sectoral – estimates range between 0.3 and 0.9 (Arrow et al. 1961, Klump et al. 2007, Herrendorf, Herrington, et al. 2015, Alvarez-Cuadrado et al. 2018, Oberfield and Raval 2021), and between 1.25 and 1.6 (Piketty 2013, Karabarbounis and Neiman 2014), passing through a unitary value (Berndt 1976). Moreover, as outlined in Oberfield and Raval (2021), it is unclear whether time-series or micro-level data should be used.

rate of non-routine ones, while this is not the case for bottom industries, and even less true for middle industries. Estimated values for the elasticities of substitution allow to consider substantial differences in the degree of structural transformation across industries, implying an heterogeneous rate of reallocation of economic activity towards selected industries: this reallocation is driven by differences in prices and quantities of capital-labour pair at industry level, which are captured by the trends in the considered labour share measures. More, estimates are consistent with the prediction of the wage determination in eq. (10): an industry, to have higher wage premium, should have a low ρ and an high σ.

Matching moments. To conclude the outlined calibration, the left-outside parameters are estimated by matching salient moments in the data in the spirit of the procedure drawn by Mc Fadden (1989), the *Method of Simulated Moments* (MSM). These parameters refer to each weight $(\mu_s, \lambda_s)_{\forall s}$ in the production function, plus the parameter governing the dispersion in households' idiosyncratic productivities (θ) that drives the strength of sorting and segregation effects. Given the estimated values for the parameters so far, the calibration schedule leaves out with seven parameters to be identified, so as to match seven moments: each λ's is related to the ICT capital share of the related group of industries; each μ's is related to the industry group-specific measure of routine workers by exploiting the associated theoretical definition in eq. (6); finally, since θ expresses the productivities' dispersion degree and thus labour market polarization due to sorting-segregation tuple, I link its value to the routine real log-wage premium of top relative to the bottom group.[47]

To match key moments of the production structure and households' productivities specification, the method estimates the vector of parameters $\tilde{\Theta} = \left\{\lambda_s\,,\, \mu_s\,,\, \theta\right\}$ associated to any group, $s = \left\{bot, mid, top\right\}$, of industries by minimizing the *loss function*

$$\mathcal{L}\left(\tilde{\Theta}\right) = \left(\widehat{m}\left(\tilde{\Theta}\right) - \tilde{m}\right)' \mathbf{W} \left(\widehat{m}\left(\tilde{\Theta}\right) - \tilde{m}\right)$$

to reckon $\tilde{\Theta}$ that is, to minimize the distance between the estimated moments $\widehat{m}(\tilde{\Theta})$ and the data moments counterpart, $\tilde{m}$. Element $\mathbf{W}$ is an *efficient weighting* matrix that allows to implement an efficient estimator.[48] Table C.2 summarizes the resulting output, and compares the targeted data moments (expressed as mean values throughout the period 2003-2022) with that in the model; the estimation procedure well reach targeted moments, meaning that parameters are correctly identified given the assumption around the link between theory and data.

Of particular interest is the value of θ: as noticed, it can be interpreted as the degree of labour market concentration driven by both sorting and segregation effects

[47] In the model, variability in households' productivity is intrinsically connected to sorting and segregation choices. More, the dynamics of labour market concentration for aggregate employment is well replicated by that of routine workers at 3-digit US 2017 NAICS industry level; refer to Figure 5.

[48] Practically, I first set it to be an identity matrix whose diagonal elements are the mean values of each moment in the data, to then update these values using the estimated vector valued function with the distance between data and simulated moments.

working through the dispersion of households' productivities, thus determining the (average) labour supply elasticity of households for each firm-industry combination. Recalling that $\theta > 1$ I estimate an high value meaning that, over the considered time window, households do not have highly heterogeneous productivity levels and thus their choice to get a job in a specific industry instead of another is stronger. Strictly speaking, the farther θ is to 1, the more labour market is polarized in terms of workforce characteristics (stronger sorting and segregation factors): my estimate of $\theta = 11.3$ points for a solid labour market concentration (as in Figure 3), in line with the quantification in Yeh et al. (2022) for the US labour market.[49]

Comparative discussion of the calibration. A summary of the parametrization of the model can be found in Table 4: what this calibration shows is that top industries (referred to as those whose real wage has increased the most over the considered time span) are those with the highest ICT capital-non routine workers complementarity (ρ) and, at the same time, those which, exploiting such feature, are more keen to substitute out routine workers in the place of non-routine job tasks (σ). The opposite situation results if considering bottom industries: these have substantial ICT capital and non-routine workers complementarity, but such degree is complained by a weaker "gross complementarity" effect with routine workers. These findings well align with the styled facts that I have presented in the empirical motivation in Section 1: the share of non-routine over routine workers (the *task-ratio*) is changing within industries (Fact n. 2), but if such change is not accompanied by an increase in the ICT over non-ICT capital share (the *ICT capital-ratio*), then real wages of a given industry will not increase as much as another given industry in which these changes are occurring (Fact n. 3).

Moreover, a considerable share of physical capital is present in the production plan of top industries (α), alongside with the lowest weight of routine workers (μ). The wide importance of physical capital besides the estimated weight of routine workers in top industries is hiding the role of automation, even if the ambiguous effects of automation are prevalent if one looks at other groups: for example, the bottom group's share of non-ICT capital is of intermediate relevance, but also the largest role of the routine workers' weight.[50] A latent indicator of automation effects is also the estimated ICT capital weights in the production of the ICT composite good (λ) since they reveal that industries in which real log-wages have grown the most are weighting less ICT capital. Overall, the MSM calibration is a direct implication of the estimated elasticities of substitution, but also of the assumption that routine workers are neither complement nor substitute with physical capital.

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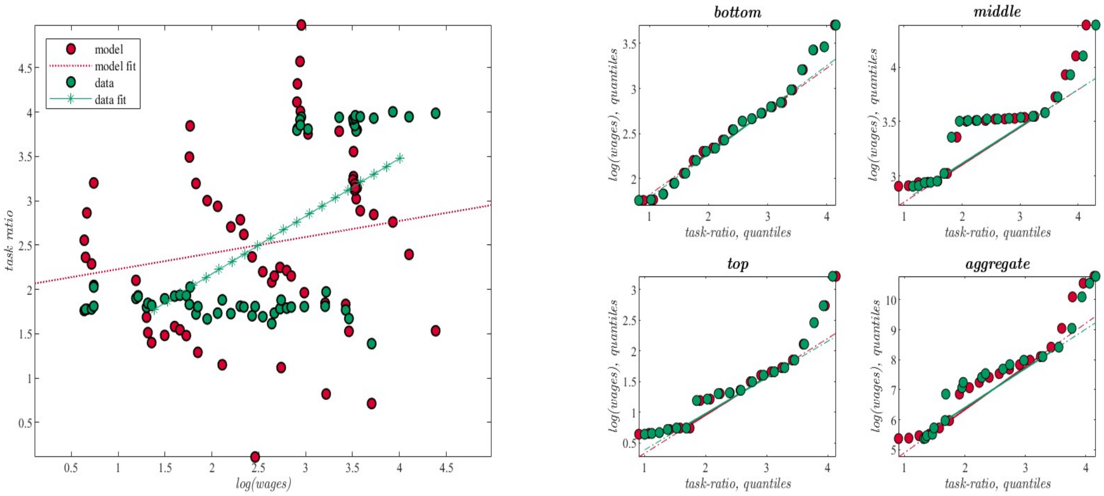
[49] Authors detect how concentration – due to employer market power, referred to as aggregate markdown (ratio between wages and marginal revenue product of labour) –, decreased between 1977 and 2002, but thereafter it has been sharply increased. Such turn is well captured even at industry level (see Figure 5).

[50] Automation (industrial robots and artificial intelligence) favours a dismissal of routine jobs and rises the employment share of non-routine workers. At industry level, the literature is unclear on the employment growth or reduction, or whether the effects depend on the type of industry; see Filippi et al. (2023) for a detailed review and discussion on the effects of automation. Henceforth, in this model automation effects are indirectly measured only through changes in $(\alpha_s, \mu_s, \lambda_s)_{\forall s}$.



(A) Task Ratio vs. Wages

(B) Quantiles

Figure 4: Model and data comparison

Note: this figure shows the comparison between the model series and the related series in the data. Panel (a) represents the correlation in the baseline equilibrium between the task ratio (non-routine over routine tasks) with the empirical and model-implied real *log*-wage level, and the corresponding lines show the linear fit of the correlation; Panel (b) plots the parametric curves associated to quantiles of the considered HP-filtered series (model vs. data) one against each other. Series are scaled to be in the same range for graphical comparison. All plots consider industries to be grouped in terms of bottom, middle, and top industries' groups. Red circles refer to the model, while red ones to the data.

3.3. Model fit

The validity of the calibration strategy can be assessed by checking the strength of such estimated and calibrated parameters by referring to how the model performs in targeting some other data moments. In particular, I study how the model compares to the US group of industries in the considered sample when addressing moments that were not targeted in the estimation procedure. Table C.3 reports how the model-related moments coincide with the untargeted data moments, expressed as percentage changes from the initial to the final steady states.[51] Model performance captures very well the direction of the untargeted moments in the data. I pick all the moments related to the wage structure in the economy, and evaluate the fitting also at the industry-group levels. The only moment the model is not able to target is those related to non-routine wages of the middle group: as I argue in Appendix E, industries in middle group are those suffering the most from business cycle and the model I built, without additional assumptions and stochastic components, is not allowed to capture cyclical fluctuations in economic activity. An important observation is that almost all the appraised wage-moments have negative slope, thus linking my model to the secular decline in real wages (*e.g.*, Massenkoff and Wilmers 2023). The only increasing moments are the "top/bottom wage ratio" and the "aggregate task premium" (reflecting the wage premium of non-routine over routine tasks), making

[51] Further untargeted moments are in Tables 6 and C.7; still, data approximation is good.

TABLE 6: IMPLIED FIT OF WAGE VARIANCES

moment	***data***	***model***
routine wage variance, across industries	2.285	2.289
non-routine wage variance, across industries	2.314	2.311
between-industry wage variance	2.299	2.300

Comparison of the model fitting against data for moments related to 3-digit US 2017 NAICS between-industry real $\log$ wage variance structure over the period 2003-2022; variances are computed according to eq. (2). The first two rows compute this measure for routine and non-routine tasks, while the last row directly reports the wage dispersion across industries.

the model suitable for studying the evolution of this wage gap.

Another central hypothesis to validate in the cross-section is the model's ability to capture an increase in industry real log-wage following a rise in the task ratio, as discussed in Section 3.1. To this end, Panel 4a plots the correlation between the share of non-routine workers over the mass of routine workers and the industry wage as both in the data and in the model. Imposed model structure is able to successfully replicate the upward-sloping correlation implied by the data, an indicator of having implemented the correct strategy to calibrate all the parameters featuring the model.

Wage variances. Finally, the primary scope of the model is to detect the industry's determinants that account for between-industry wage inequality, moment not directly targeted in the MSM parameters' estimation. Table 6 reports the fitting of real log-wage variance across industries for routine and non-routine workers, as well as that for industry-specific wage rates. Tasks' specific variances are computed according to eq. (2) given the analytical wage series sparking from eq. (10), while the between-industry wage variance is found by averaging these two dispersion indicators. Given the calibrated values of parameters, the model built has the virtue of well targeting all the considered measures of inequality on real log-wages.

To conclude, the model performs well in replicating both targeted and untargeted moments related to the wage structure of the US economy over the period 2003-2022: fitting is detected either at the aggregate and industry levels, and also for differences among routine and non-routine workers.

4. COUNTERFACTUAL ANALYSIS

The purpose of the present analysis is to understand whether heterogeneity in the industrial composition of the US economy has effect on the observed trends in wage inequality. To this end, I perform a counterfactual analysis to evaluate the contribution of variations in structural parameters on the levels of between-industry wage inequality in US. In particular, I fully re-estimate the set of parameters in the model over two different time-periods, and compute the associated moments implied by the fully re-estimation procedure when switching on the change in one or more parameter at time while fixing the others.[52] Central scope of this section is to identify the main drives of wage-related variance at industry level, and then compute the fraction of the data explained by the structural model built.

In the set of counterfactual exercises the parameters I am focusing on are three: the elasticity of substitution between ICT capital and non-routine labour input, *i.e.*, the CES composite, namely ρ; the elasticity of substitution between routine and non-routine labour inputs, namely σ; and the productivity dispersion of the households (a proxy of sorting and segregation effects, and thus of labour market concentration), namely θ. I evaluate their contribution both alone and in joint combination: variations in the industry-specific elasticity of substitution parameters, $(\rho_s, \sigma_s)_{\forall s}$, have the aim to analyse, to explain and to quantify – absent any changes in price and quantity of any elements in the industry production function in eq. (9) – the importance of structural transformations among industries. Changes in θ quantify the pattern in the degree of labour market concentration: since industries face not perfectly elastic labour supplies, as the labour market becomes more concentrated it must be the case that labour supplies become more industry specific under stronger sorting-segregation tuple.

4.1. Selecting parameters

To give a sense of these choices in Table 7 I present evidence of the relevance of the changes occurred in the two elasticities of substitution (ρ, σ) considering two separate time windows, 2003-2012 and 2013-2022, that split the whole sample in two bins of equal size. It turns out that top industries experience a marked variation in only one elasticity: on the one hand complementarity between ICT capital and non-routine workers has decreased; on the other hand, in compensation of such drop, this group experiences a pale shift in the "gross substitution" between routine and non-routine workers. Different case is for the middle group, where non-routine workers have increased their degree of complementarity with ICT capital, and a very pale negative shift in the complementarity (higher gross substitutability) between routine workers and their "tech counterpart". Finally, bottom group has undergone a drop in the substitutability among job types, together with a marked drop in its degree of complementarity between ICT capital and non-routines.

Intuition behind substantial variations in labour market concentration can be gained from Figure 5, which computes the Herfindahl-Hirschman Index (HHI) for labour market competitiveness by worker types and aggregate employment.[53] Since θ is computed via the MSM, its estimate is the mean value through the considered years thus allowing to interpret its level not only as a cross-sectional indicator, but also as a signal of the occurred variation in sorting and segregation (similar workers

[52] This exercise is presented in the main text solely for between-industry wage inequality (Tables 8 and C.10). In a different manner, in Appendix C I apply the same exercise on between-industry wage variance considering both routine (Table C.11) and non-routine (Table C.12) workers separately.

[53] Further details are provided in Appendix C.

TABLE 7: TIME-VARYING ESTIMATION

	2003-2012		2013-2022	
	β^{ρ}_{ζ}	β^{σ}_{ζ}	β^{ρ}_{ζ}	β^{σ}_{ζ}
bottom	.355 [.12]	.366 [.12]	.819 [.05]	.326 [.06]
middle	.431 [.04]	.429 [.08]	.345 [.04]	.438 [.09]
top	.408 [.04]	.367 [.12]	.508 [.06]	.358 [.05]

Estimation of the elasticities of substitution as given in eqs. (12) *and* (13) *over different time span (2003-2012 and 2013-2022), in absolute values, for 3-digit US 2017 NAICS industries. Standard errors in parenthesis,* $[\cdot]$, *and* 95% *confidence interval significant but not reported.* $\widehat{\rho}$ *refers to the estimate of the pair* $\left(\ell(nrt,s)\,;\,k(ict,s)\right)$, *and it exploits the degree of substitutability between non-routine workers and ICT capital;* $\widehat{\sigma}$ *relates to the pair* $\left(\ell(rt,s)\,;\,[\ell(nrt,s),\,k(ict,s)]\right)$, *and it is the degree of substitutability between routine workers and the joint combination of non-routine workers and ICT capital.*

are employed in the same industry under stronger effects). By considering two separated periods of the sample (2003-2012 and 2013-2022), a clear division emerges: a steady increase in labour market concentration characterizes the first half, while a smoothing behaviour materializes later on (green line), and this is due to the drop in concentration of non-routine workers (blue line). More, the re-estimation of θ over both half of the sample reports values of $\theta_{\text{2003-2012}} = 7.26$ and $\theta_{\text{2013-2022}} = 7.79$ meaning that, in the lights of Figure 5, the variation occurred in industry-level concentration of workers has been higher in the first half of the sample, and lower in the later period; still, estimated labour market concentration is sizeable, with an increased concentration (but flat or moderate in the last decade) over time.[54] Interpretation of the figure suggests that, to keep track of economy-wide labour market concentration it is sufficient to look at the routine task concentration; estimated via the top/bottom industry wage ratio for routine jobs, such observation relates to the level of θ, in confirmation of the strategy I design to compute its calibrated value. Hence, heterogeneous changes in (ρ, σ) pair coupled with variations in θ can be interpreted as capturing the reallocation of capital and worker types across industry alongside the structural increase in labour market concentration of routine and non-routine tasks: if considered altogether, such combination would account for a substantial margin for uneven industry wage premiums.

Key is to understand the role of differential adoption of structural changes. As a preview of the results, when considering industry-heterogeneous patterns in both elasticities: firstly, changes in both ρ and σ explain a marked fraction of real log-wage variance but, secondly, it is the joint change in the two elasticities that explains major shares of wage inequality for the US economy. Moreover, given these patterns,

[54] Remember that $\theta > 1$: as it approaches to 1, labour market concentration decreases. Hence, the two estimates of θ are consistent both with the theory and the figure: the concentration of workers at industry level is higher in the second half ($\theta_{\text{2013-2022}}$) than in the first one ($\theta_{\text{2003-2012}}$).

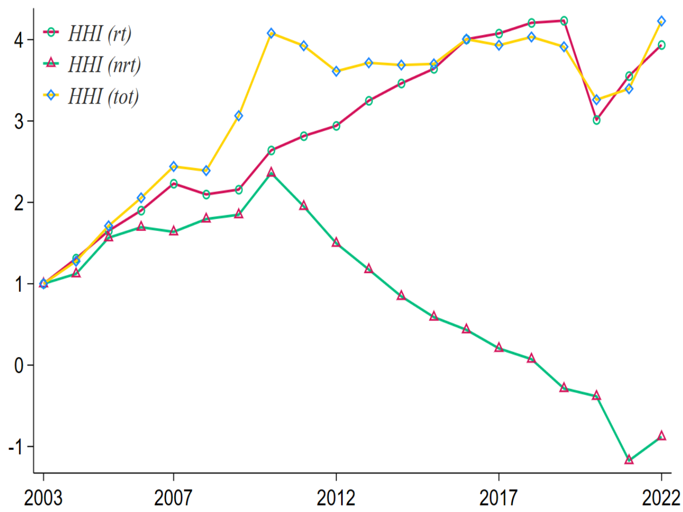


FIGURE 5: LABOUR MARKET CONCENTRATION AS A STRUCTURAL CHANGE

Note: this figure represents the evolution in labour market concentration as measured by the Herfindahl-Hirschman Index (HHI) – on the y-axis – by routine and non-routine (red and green lines, respectively) job tasks, and by total employment (yellow line). Series are normalized relative to their initial value in 2003, set to 1. *Source*: BLS and own calculations.

major labour market concentration in terms of stronger sorting and segregation effects would worsen the level of wage inequality.

4.2. INSPECTING THE MECHANISM: MODEL RE-CALIBRATION

Central exercise is to re-estimate all the model parameters for two equal portions of the sample (2003-2012 and 2013-2022), and compute the differences implied by changing only one or more parameters at a time; new values are reported in Table C.6. This analysis is well suited to link the data-driven shifts in structural transformations across US industries with empirically-observed trends in wage inequality as predicted by the model. Main scope is to quantify what would have been the total variance if only a specific parameter changes from period 1 to period 2, keeping the remaining parameters fixed at their initial level. In other words, given the re-estimated parameters, consider the following model

$$\Delta var\left(w(s) - \overline{w}\right) = f\left(\Phi_s\left(x, \tau_1\right), \Theta_s(p, \tau_1), \Phi_s\left(x, \tau_2\right) \,\middle|\, \Delta\Theta_s\left(p_{\tau_2}^{\{\rho,\sigma,\theta\}}, -p_{\tau_1}\right)\right) \quad \text{(Model A)}$$

where the change in between-industry wage variance is a function of the input factor series in both periods, $\Phi_s\left(x, \tau_1\right)$ and $\Phi_s\left(x, \tau_2\right)$, the whole set of parameters in period 1, $\Theta_s(p, \tau_1)$, and the set of parameters when considering some of them in the second period keeping fixed the others, $\Theta_s\left(p_{\tau_2}, -p_{\tau_1}\right)$, for any industry-$s$. Practically, given the change in capital and labour types, I estimate the wage levels and variances with two set of parameters: *(i)* full set related to period 1, and *(ii)* full set related to period 1 with one (or a combination) related to its period 2 level; parameters are those selected in Section 4.1.

TABLE 8: MODEL COUNTERFACTUAL, CHANGE

		Δ ***model*** $\mid \Delta\, m\Big(\Phi(x,\tau_2), \Theta = \{p_{\tau_2}, -p_{\tau_1}\}\Big)$		
industry wages	$var(w)_{\tau_2}$	*level*	*share, model*	*share, data*
DATA	1.18			
MODEL	1.09			
$\Delta\sigma$		2.37	2.18	1.99
$\Delta\rho$		.88	.81	.74
$\Delta(\sigma,\rho)$		1.12	1.03	.94
$\Delta\theta$		1.34	1.23	1.13
$\Delta(\sigma,\rho,\theta)$		1.16	1.07	.98

Quantification of Model A. Model implied between-industry real log-wage variance changes between two time spans differently calibrated, and changes also according to variations in some parameters; values are referred to variance levels considering bottom, middle, and top industries. Column 2 shows the level in the second period of the between-industry variance both in the data and in the period-two fully calibrated model. For the model specified in column 1: column 3 represents the variance level in the second period as implied by the change in the parameter(s), while column 4 computes the second period variance share of the period-two full model which is accounted by the change in a specified parameter, $\frac{m\left[\Phi(x,\tau_2) \mid \Theta(p,\tau_2), \Theta(-p,\tau_1)\right]}{m\left[\Phi(x,\tau_2) \mid \Theta(p,\tau_2)\right]}$*, where $\Phi(x,\tau_2)$ identifies the series in the second period, and Θ the set of parameters where some of them, (p,τ_2), are taken in the second period, while $(-p,\tau_1)$ reflects the set of all the parameters in the first period but those considered in the second period. Column 5 reports the fraction of variance explained by changes in parameter(s) in the observed data-driven variance.*

Results are reported in Table 8. Second column shows the between-industry variance of second period (τ_2) in both the data and the model specified in column 1. To evaluate the role of each structural parameter, column 3 reports the model-implied wage variance by imposing all the parameters to be in period 1, but the parameter(s) of interest being at period 2 level. The predictions arising from this estimation, considering industry-heterogeneous pattern in the substitutability of factors of production, suggest that, to account for trends in US between-industry wage inequality, a pivotal role is played by ρ and σ jointly, and thus by observed changes in the substitution elasticities between ICT capital, routine and non-routine workers. In fact, unique changes in ρ would have determined a substantial level of between-industry wage variance (.88), while larger impact is devoted to changes in the parameter governing the routine-non routine labour force substitution: alone, industry-specific changes in σ would have rather implied a massive level of wage dispersion (2.37). Given these opposite-in-size effects, and considering jointly the shifts in both parameters, then the implied between-industry real log-wage variance (1.12) would have been closer to that implied by the full calibration model (1.09) and by the data (1.18).

Column 5 quantifies the importance of each parameter in explaining the observed trend in US wage inequality since it shows the share of the model real log-wage variance implied by shift in parameter(s) in the empirical data variance. While unique changes in ρ account for 74%, heterogeneous shifts in both elasticities are able to capture the 94% of the data-implied level of between-industry wage variance (103% of the full calibrated model for the second period, 2013-2022). These findings suggest that major wage differentials among industries are due to different and industry-heterogeneous degrees of substitution between routine and non-routine workers, rather than the degree of substitution between ICT capital and non-routine labour force; the combination of such variations in these two parameters accounts for a major share of the observed trend in wage inequality.

Above conclusions directly bridge to the interpretation of changes in θ, whose value shifts from $\theta_{2003\text{-}2012} = 7.26$ to $\theta_{2013\text{-}2022} = 7.79$; alone, stronger workers' concentration measured by such positive change would mostly surge real log-wage variance (1.34) but, when such sorting and segregation effects (due to a reduction in households' productivity dispersion) are accompanied by an heterogeneous pattern of the elasticities of substitution as suggested by Table 7, its effect would slightly sharpen the explained economy-wide between-industry wage inequality (accounted level of 1.16 in the model); put it differently, given heterogeneous changes in substitutability parameters' degrees, a highly concentrated labour market induced by stronger worker types' sorting and segregation factors increases overall inequality in labour income. Henceforth, considering only variations in industry-specific structural characteristics (through simultaneous changes in both elasticities of substitution) in combination with those in the labour market resilience (as measured by sorting and segregation effects via workers' concentration), the model predicts that the joint component $\Delta(\sigma, \rho, \theta)$ is able to explain 98% of the data-implied US between-industry variance of real log-wages.

Sensitivity. So far the analysis has considered just variations in the three core parameters $(\rho_s, \sigma_s, \theta)_{\forall s}$ of the model while switching off occurred variations in the values of production function parameters $(\alpha_s, \mu_s, \lambda_s)_{\forall s}$ which, as explained in Section 3.2, may underlies the potential role of *automation*. All the above results are further reinforced by the reverse exercise, in which I conjecture what would have been the total variance if only a specific parameter is fixed at its initial level, letting the remaining parameters free to change from period 1 to period 2, that is

$$\Delta var\Big(w(s) - \overline{w}\Big) = f\Big(\Phi_s\left(x, \tau_1\right), \Theta_s(p, \tau_1), \Phi_s\left(x, \tau_2\right) \Big| \Delta\Theta_s\left(p_{\tau_2}, -p_{\tau_1}^{\{\rho,\sigma,\theta\}}\right)\Big) \quad \textbf{(Model B)}$$

and results are presented in Table C.10:[55] absent any change in σ – thus giving a first order role to the combination of changes in ρ and θ with that of the weights and income shares in the production function, heterogeneous across industries –, total accounted variance would have been closer to the actual in the data explaining 79% of the occurred trend, while fixing the combination of the two elasticities $\left(\Delta\Theta_{|(\sigma,\rho)}\right)$, total variance explained would have been notably higher (1.31) to the actual variance in both data and model; same result is found when fixing all the parameters of

[55] Such counterfactual analysis, differently from that in Table 8, allows to consider also changes in the production function weights, which are industry-specific too. In other words, this exercise considers both changes in structural $(\rho_s, \sigma_s)_{\forall s}$ and in production $(\alpha_s, \mu_s, \lambda_s)_{\forall s}$ parameters, besides the usual change in households' productivity dispersion measured by shifts in θ.

interest (thus considering only the role played by income shares, α, μ and λ), namely (σ, ρ, θ). Finally, keeping constant the productivity dispersion parameter (θ), thus letting the two elasticities and the other industry-specific parameters to vary, most of the total variance would have been explained, in line with the stylized facts presented in Section 1: considering only industry-heterogeneous changes in both the substitution-elasticities and the weighting parameters, a share of 88% of the data-implied US between-industry wage variance can be explained (96% in the model).

Investigations in this section outline an important feature of the US wage structure: observed structural differences among industries account for a sizeable fraction of wage inequality. Bridging the model to the data, most of the inequality is accounted by trends in industry-heterogeneous differentials in elasticities of substitution among capital and worker types (94%, Table 8), also taken in combination to different weights of factor inputs in production (88%, Table C.10). Considering these differences across industries, the rise in labour market concentration in terms of stronger workers' complementarities (sorting and segregation) is an amplifier of US wage inequality in the last two decades, explaining 98% of the total between-industry real log-wage variance (Table 8).[56]

The role of labour market power. Model specification allows also to inspect whether the assumption of monopsony power by the part of firms is a dimension worth to analyse in order to account for between-industry wage inequality. Labour market failures due to employers market power in wage-setting decision are recognized by the on-going debate (*e.g.*, Prager and Schmitt 2021, Dodini et al. 2021), while Card, Rothstein, et al. 2024a argue that, in several manufacturing industries, variations in industry wage premiums are not positively correlated with that of wage markdowns. In Appendix D I replicate the exercises so far when considering a version of the model in which monopolistically competitive firms (h, s) do exploit monopsonistic power thus choosing its optimal wage level. In terms of eq. (10), monopsonistic power results in displaying a (average) wage markdown over the marginal revenue product of labour of

$$\mathcal{M}^{\theta} = \frac{\theta}{1+\theta} \in (0, 1)$$

which is increasing function of the labour supply elasticity θ (as, among others, in Card, Cardoso, Heining, et al. 2018 and Berger et al. 2022). Referring to Figure 3, as $\theta \to 1$ households' productivities are more dispersed and the labour supply elasticity to changes in relative wages is higher, so that monopsony power decreases as well as the wage markdown. Results under monopsony are mostly unchanged compared to the main analysis both in the direction and in the magnitude, thus suggesting that between-industry real wage inequality is not a direct consequence of

[56] Outcomes are almost unaffected – in the direction but not in the magnitude – when considering between-industry wage dispersion for routine (Table C.11) and non-routine (Table C.12) tasks separately: changes in (ρ, σ) have an averaged impact for routine workers, while sorting and segregation effects are more pronounced for non-routines. Results are shown in Appendix C.

monopsony power exploitation of employers. The presented result may point towards a significant effect of monopsony once allowing for heterogeneous employers' wage-setting degree, thus considering a local measurement in monopsony power.

4.3. Skill-Biased Technological Change

Finally, I turn to evaluate the systematic effect of Skill-Biased Technological Change (SBTC). In fact, a final dimension that can be inspected through the model is how and whether changes in capital and labour series at a time are affecting between-industry wage inequality when shutting down the evolution in production technology parameters $(\alpha, \mu, \lambda, \rho, \sigma)$ and labour market concentration (θ). Given the re-estimation procedure, consider the following model

$$\Delta var\Big(w(s) - \overline{w}\Big) = f\Big(\Phi_s\left(x, \tau_1\right), \Delta\Phi_s\left(x_{\tau_2}, -x_{\tau_1}\right) \Big| \Theta_s\left(p, \tau_1\right)\Big) \tag{Model C}$$

where the change in between-industry wage variance is a function of industry-specific factor series, $\Phi_s\left(x, \tau_1\right)$, and parameters, $\Theta_s(p, \tau_1)$, taken in period 1, while considering one (or a combination of) series at the second period level while keeping fixed the others, $\Phi_s\left(x_{\tau_2}, -x_{\tau_1}\right)$ to first period.

Table C.13 reports the outcome, and it has to be interpreted like in the previous section, where column (2) shows the between-industry variance of second period (τ_2) in both the data and the model while, for the changes in each series considered in the first column: columns (3), (4), and (5) report the implied wage-variance level, the variance share of that in the "all-series" model, and the explained variance of the data, respectively. Routine workers differentials alone inflate wage inequality (2.62) and, to a little extent, it does also ICT capital series (1.69). Combinations of both labour types, also together with ICT capital explains more than the actual real log-wage variance (112% and 113%). Compared to Table 8, reported "changing-series" shares of data-driven wage variance are substantially higher than that considering *also* changes in substitution elasticities and sorting and segregation effects, meaning that *Skill-Biased Technological Change* (SBTC) *overestimates the actual between-industry real wage inequality*. In this regard, changing in the series are necessary but not sufficient to fully determine the (change in) magnitude of real log-wage variance: central considerations to consider within this approach are not just the systematic changes in capital and labour quantities along technological change, but key are also the changes occurred in structural transformation parameter, uneven across industries. This will become clearer in the next section, where I am going to recompute the between-industry wage inequality completely turning off the channel of heterogeneous structural parameters among industries, thus considering just the occurred variations in factors of production.

5. Factor quantities and productivity changes

A concluding step that allows to close the analysis to disentangle the main channels of the US between-industry wage inequality is to consider to which extent divergences in the inputs of production are important when imposing industries to have the same structural parameters. Given τ_0 being the initial year (2003) of the sample,

$$var\Big(w(s) - \overline{w}\Big) = f\Big(\Delta\Phi_s\left(x\right), \Phi_s\left(-x, \tau_0\right) \Big| \Theta_{=\forall s}\left(p\right)\Big) \qquad \text{(Model D)}$$

Stated differently, I conjecture what would have been the total real log-wage variance across industries if only a specific series – capital and labour types, or a combination – changes over time, $\Delta\Phi_s\left(x\right)$, keeping the remaining series fixed at their initial level, $\Phi_s\left(-x, \tau_0\right)$, and imposing economy-wide values for calibrated parameters, $\Theta_{=\forall s}\left(p\right)$. In the exercise presented below, these are the mean value for both each parameter estimated through MSM approach ($\mu = .503$, $\lambda =, 458$, and $\theta = 11.3$), and for physical capital's income share ($\alpha = .324$), with the price markup parameter fixed to $\epsilon = 6$. Considering all the industries not divided in group, elasticities of substitutions have been estimated again, and set to $\rho = .333$ and $\sigma = .595$.[57]

Table 9 reports a model-decomposition of Table 6 as proposed in Model D. A discussion of this counterfactual exercise reveals that: shifts in just industry-specific routine workers account for the major variation compared to other series, and little is the magnitude of non-routine workers' dynamics, $\Delta\ell(nrt)$, even when combined with shifts in ICT capital, $\Delta(tech)$. Substantial seems to be the impact of divergent ICT capital across industries, but still meaningless in terms of observed real log-wage variance. Overall, it can be stated that industry-specific differentials in the adoption of ICT capital and in their employment dynamics for both routine and non-routine job tasks are able to quantitatively account for 6% to 15% of the observed real wage inequality either across industries or across tasks.[58]

Productivity differentials. So far all the analysis has been centred on excluding total factor productivity (TFP), while last two columns report the industry-specific changes in productivity; such patterns cannot be directly observed in the data, but sectoral series can be recovered from the theoretical model. Start by noting that Proposition 1 allows to write the industry-level counterpart of eq. (9) as

$$y(s) = A(s)\, f\Big(k(phy,s), k(ict,s), \ell(rt,s), \ell(nrt,s) \mid \Theta_s\Big)$$

---

[57] Values computed when drawing Figure C.1. Standard errors are respectively equal to $Std.Err._{(\rho)} = .02$ and $Std.Err._{(\sigma)} = .03$, with 95% confidence bands of $[.301, .366]_{(\rho)}$ and $[.545, .645]_{(\sigma)}$. Note that Table 9's results hold also when re-estimating all the parameters for the whole economy (see Table C.15), thus not considering the mean values of the calibration performed in Table 4.

[58] An analogous exercise, weighting each capital and labour series considering heterogeneous differences in structural parameters (Table C.9), reaches almost these results: routines and ICT capital series appear to be slightly prevalent in enlarging the variance share of about 5-20%. However, even when all the series are fixed over time, the model barely overestimate the variance level, meaning that structural parameters appear to be more relevant in addressing the level of wage inequality both across industries and job tasks.

TABLE 9: MODEL VS. DATA COUNTERFACTUAL, SERIES

		model $\mid \Delta\,\Phi(x)$						
							$\Delta\,(tfp)$	
	data	$\Delta\ell(rt)$	$\Delta\ell(nrt)$	$\Delta\,(\ell)$	$\Delta k(ict)$	$\Delta\,(tech)$	*mean*	*baseline*
WAGES, VARIANCE								
routine	2.285	.35	.16	.22	.24	.15	.25	.22
non-routine	2.314	.32	.12	.17	.23	.13	.21	.23
industry	2.299	.33	.14	.19	.23	.14	.23	.23

Quantification of Model D. Changes in variances in real log-wages in the model induced by variations in one or more series, keeping fixed the others, and imposing the mean parameters to be homogeneous across industries. $\Delta\,(\ell)$ refers to joint variations in routine and non-routine series, $\Delta\,(tech)$ is associated to simultaneous changes in both ICT capital and non-routine workers, while changes in estimated industry-specific Hicks-neutral exogenous total factor productivity (TFP), given eq. (14), are captured by $\Delta\,(tfp)$; TFP series are taken under the same (mean) parameters' values, or given the baseline calibration (Table 3.2). In all the columns, the variation is computed throughout the period-by-period percentage differential thus identifying overall changes in empirical trends implied both by the data and the model; same values differ in terms of decimals.

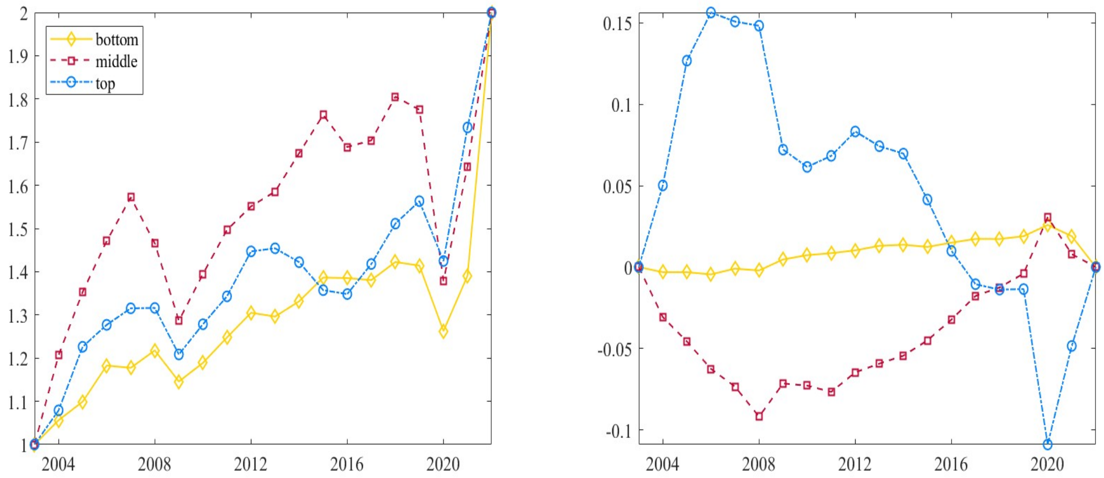
where $A(s)$ is an exogenous measure of product-augmenting Hicks-neutral TFP for industry-s, $k(j,s)$ and $\ell(a,s)$, for $j = \{phy, ict\}$ and $a = \{rt, nrt\}$, are its quantities of capital and labour types, and Θ_s identifies the vector of calibrated and estimated parameters.[59] Using industry-by-industry data on the annual, seasonally adjusted value added extracted from BEA to measure output, $y(s)$, it is possible to recover the year-by-year series for sectoral productivity from

$$\begin{aligned} log\Big(A_t(s)\Big) &= log\Big(y_t(s)\Big) - log\Big[f_t\Big(k(phy,s), k(ict,s), \ell(rt,s), \ell(nrt,s) \mid \Theta_s\Big)\Big] \\ &= log\Big(y_t(s)\Big) - \alpha_s\, log\Big(k_t(phy,s)\Big) - (1-\alpha_s)\; log\Big(v_t(s)\Big) \end{aligned} \tag{14}$$

where $v_t(s)$ comprises the relation among ICT capital, routine and non-routine workers along the parameters governing their associated weights, the different elasticities of substitution, and the degree of labour market concentration.

Estimated series for $s = \{bot, mid, top\}$ are in Figure 6. Panel 6a displays the estimated series under the same industry-level calibrated parameters, while Panel 6b computes the differences between these TFP measures and that estimated using the baseline calibration of Table 4. In both estimations, and evenly among industries, TFP is increasing over time but a marked drop in 2008 (Great Financial crisis) and 2020 (COVID-19 crisis); little discrepancies are found among the two TFP measures, more marked for top and middle industries. On the right border of Table 9 is reported the magnitude of shifting industry-specific productivity measures for both

[59] Neutrality in the sense of Hicks (1932) implies that the marginal rate of substitution between capital and labour inputs is not altered, and hence including productivity does not pose threads to the parameters' identification strategy of Section 3.2, which may be confounded by other forms of neutrality (labour-augmenting Harrod-neutrality, or capital-augmenting Solow-neutrality).



(A) UNIQUE CALIBRATION, MEAN

(B) DIFFERENCE WITH BASELINE

FIGURE 6: ESTIMATED PRODUCTIVITIES

Note: this figure shows the estimated Hicks-neutral exogenous total factor productivity (TFP) measures estimated from the model. Panel (a) plots the series given a calibration where all the parameters are evenly set at the same *mean* values for all the industry-groups, while Panel (b) shows the difference between such series and the estimated TFP measures using the baseline calibration reported in Table 4. Series are scaled to be in the same range for graphical comparison.

types of calibration: as in the case of factor quantities, isolated changes in TFP are meaningless in order to address the real log-wage variance in the data.

Overall, the purpose of this section is to unearth the role of industry-specific patterns in capital, labour, and productivity differentials on wage inequality when all the residual differences in terms of parameters are turned off. Strikingly, single and combined shifts in the series are able to address between 6% and 15% of the variance level in the data, thus reinforcing the conclusions of Section 4 which point towards a massive involvement of heterogeneous (cross-sectional and trend levels) differences in structural parameters to address the observed between-industry wage inequality.

CONCLUDING REMARKS

Changes in wage inequality for the US economy observed over the last decades have been considerable and brought to a renewed attention on their origins. The literature has started to identify the rise in differences across industries as the dominant driver of the increasing inequality. Rationale relies upon the role of structural transformations as a principal mechanism to interpret observed changes in US labour market and in its wage structure. I conceptualize this framework in a general equilibrium model, exhibit heterogeneous degrees of substitutability between capital and labour types, and the economy is characterised by certain degree of labour market concentration which, in turn, gives birth to stronger sorting and segregation effects, a consequence of imperfect flexibility of labour supply.

A structural estimation of the model successfully reproduces the wage structure of the US economy, capturing the empirical wage inequality across industries. It is demonstrated that such inequality is primarily attributable to structural differences among industries: specifically, trend-heterogeneous differentials in the elasticity of substitution between routine and non-routine workers emerge as a principal determinant of between-industry wage variance; conversely, the effect of varying substitutability between ICT capital and non-routine workers is comparatively limited. Combined shifts are capable to capture 94% of the real log-wage variance observed in the data. Furthermore, when neutralising the channel of industry-differentials in trends of structural parameters, only a modest fraction (ranging from 6% to 15%) of observed real wage variance remains explicable through imposed variations in capital and/or labour inputs, even when incorporating an estimated measure of total factor productivity (TFP) at the sectoral level. These findings strongly suggest that differences in structural parameters across industries serve as the predominant force governing the observed trend of wage inequality.

Moreover, the model also yields significant labour market implications after the inclusion of trends in the link between workers' sorting and segregation effects and wage dispersion. An increase in labour market concentration exerts only a marginal effect on wage inequality when the model accounts for trends in structural transformations across industries. More broadly, variations in both substitution elasticities and labour market concentration jointly explain nearly 98% of the observed wage inequality attributable to industry-specific factors. In addition, when industry-heterogeneous shifts in both elasticities of substitution are considered alongside that of the associated weights of capital and labour inputs in production, 88% of the data-implied between-industry wage variance is accounted for. These conclusions remain robust even when the analysis is disaggregated to examine wage inequality separately for routine and non-routine workers.

Taking a general perspective, the model detects a sizeable role for the reallocation of economic activity – specifically, shifts in the substitutability of capital and labour – in shaping real wage dispersion across industries. Besides smaller effects of the substitution across capital and workers types, the secular trend in wage inequality in the United States is primarily driven up by uneven, industry-level shifts in the substitutability between routine and non-routine workers. A possible interpretation of these findings might be that they suggest how between-industry wage inequality is largely determined by factors pertaining to the labour side of the production process.

This outcome follows directly from two fundamental elements of production: *(i)* structural technology parameters, and *(ii)* composition of capital and labour types within industries. While both aspects remain essential to a comprehensive understanding of wage inequality, I contend that the principal forces underlying its persistent rise are related to an "indirect" effect of SBTC – specifically, the degree of substitutability across job tasks and the evolution of industry-level employment composition. Further explanations on what determines structural differences among industries are called for.

References

ACEMOGLU, D. and D. AUTOR, "Skills, tasks and technologies: implications for employment and earnings", IN: *Handbook of Labor Economics*, vol. 4B, pp. 1043-1171, edited by Orley C. Ashenfelter and David Card, Amsterdam: North Holland 2011. 2, 3, 7.

ALLEN, S. G., "Updated notes on the interindustry wage structure, 1890–1990", *Industrial and Labor Relations Review*, vol. 48, no. 2 (1995), pp. 305-321. 6.

— "Technology and the wage structure", *Journal of Labor Economics*, vol. 19, no. 2 (2001), pp. 440-483. 6, 7.

ALVAREZ, J., F. BENGURIA, N. ENGBOM, and C. MOSER, "Firms and the decline in earnings inequality in Brazil", *American Economic Journal: Macroeconomics*, vol. 10, no. 1 (2018), pp. 149-189. 6, 19.

ALVAREZ-CUADRADO, F., N. VAN LONG, and M. POSCHKE, "Capital-labor substitution, structural change and the labor income share", *Journal of Economic Dynamics and Control*, vol. 87 (2018), pp. 206-231. 3, 30.

ARROW, K. J., H. B. CHENERY, B. S. MINHAS, and R. M. SOLOW, "Capital-labor substitution and economic efficiency", *Review of Economics and Statistics*, vol. 43, no. 3 (1961), pp. 225-250. 30.

ARVAI, K. and K. MANN, "Consumption inequality in the digital age", *Banque de France Working Paper Series no. 890* (2022). 28.

AUTOR, D., "The labor market impacts of technological change: from unbridled enthusiasm to qualified optimism to vast uncertainty", *NBER Working Paper No. 30074* (2022). 11.

AUTOR, D. and D. DORN, "The growth of low-skill service jobs and the polarization of the US labor market", *American Economic Review*, vol. 103, no. 5 (2013), pp. 1553-1597. 7.

AUTOR, D., L. KATZ, and M. KEARNEY, "The polarization of the U.S. labor market", *American Economic Review*, vol. 96, no. 2 (2006), pp. 189-194. 2, 7.

— "Trends in U.S. wage inequality: revising the "revisionists"", *Review of Economics and Statistics*, vol. 90, no. 2 (2008), pp. 300-323. 6.

BARTH, E., A. BRYSON, J. DAVIS, and R. FREEMAN, "It's where you work: increases in the dispersion of earnings across establishments and individuals in the United States", *Journal of Labor Economics*, vol. 34, no. S2 (2016), pp. S67-S97. 6, 19.

BELL, L. A. and R. FREEMAN, "The causes of rising interindustry wage dispersion in the United States", *Industrial and Labor Relations Review*, vol. 44, no. 2 (1991), pp. 275-287. 7.

BERGER, D., K. HERKENHOFF, and S. MONGEY, "Labor market power", *American Economic Review*, vol. 11, no. 2 (2022), pp. 1147-1193. 40.

BERGHOLT, D., F. FURLANETTO, and N. MAFFEI-FACCIOLI, "The decline of the labor share: new empirical evidence", *American Economic Journal: Macroeconomics*, vol. 14, no. 3 (2022), pp. 163-198. 8.

BERNDT, E. R., "Reconciling alternative estimates of the elasticity of substitution", *Review of Economics and Statistics*, vol. 58, no. 1 (1976), pp. 59-68. 30.

BINGLEY, P. and L. CAPPELLARI, "Earnings dynamics, inequality and firm heterogeneity", *LISER working paper n. 2022-07* (2022). 6.

BORJAS, G. J., "Self-selection and the earnings of immigrants", *American Economic Review*, vol. 77, no. 4 (1987), pp. 531-553. 18.

BRAVERMAN, H., *Labor and monopoly capital: the degradation of work in the Twentieth century*, Monthly Review Press, United States 1974. 11.

BRISKAR, J., J. RODRIGUEZ MORA, E. DI PORTO, and C. TEALDI, "Decomposition of Italian inequality", *WorkINPS papers n.53* (2022). 7, 19.

BUERA, F. J. and J. P. KABOSKI, "The rise of the service economy", *American Economic Review*, vol. 102, no. 6 (2012), pp. 2540-2569. 8, 16.

BURSTEIN, A., E. MORALES, and J. VOGEL, "Changes in between-group inequality: computers, occupations, and international trade", *American Economic Journal: Macroeconomics*, vol. 11, no. 2 (2019), pp. 348-400. 2.

CARD, D., A. R. CARDOSO, J. HEINING, and P. KLINE, "Firms and labor market inequality: evidence and some theory", *Journal of Labor Economics*, vol. 36, no. S1 (2018). 40.

CARD, D., A. R. CARDOSO, and P. KLINE, "Bargaining, sorting, and the gender wage gap: quantifying the effect of firms on the relative pay of women", *Quarterly Journal of Economics*, vol. 131, no. 2 (2016), pp. 633-686. 6, 19.

CARD, D. and J. E. DINARDO, "Skill-Biased Technological Change and rising wage inequality: some problems and puzzles", *Journal of Labor Economics*, vol. 20, no. 4 (2002), pp. 733-783. 2, 3.

CARD, D., J. HEINING, and P. KLINE, "Workplace heterogeneity and the rise of West German wage inequality", *Quarterly Journal of Economics*, vol. 128, no. 3 (2013), pp. 967-1015. 6, 19.

CARD, D., J. ROTHSTEIN, and M. YI, "Industry wage differentials: a firm-based approach", *Journal of Labor Economics*, vol. 42, no. S1 (2024), S11-S59. 4, 7, 19, 40.

— "Reassessing the spatial mismatch hypothesis", *American Economic Association: Papers and Proceedings*, vol. 114 (2024), pp. 221-225. 6.

CASELLI, F., "Technological revolutions", *American Economic Review*, vol. 89, no. 1 (1999), pp. 78-102. 6.

CERINA, F., E. DIENESCH, A. MORO, and M. RENDALL, "Spatial polarisation", *The Economic Journal*, vol. 133, no. 649 (2023), pp. 30-69. 7.

CERINA, F., A. MORO, and M. RENDALL, "The role of gender in employment polarization", *International Economic Review*, vol. 62, no. 4 (2021), pp. 1655-1691. 2, 7.

CORRADO, C., J. HASKEL, and C. JONA-LASINIO, “Knowledge spillovers, ICT and productivity growth”, *Oxford Bulletin of Economics and Statistics*, vol. 79, no. 4 (2017), pp. 592-618. 10.

CORTES, G. M., N. JAIMOVICH, and H. E. SIU, “Disappearing routine jobs: who, how, and why?”, *Journal of Monetary Economics*, vol. 91 (2017), pp. 69-87. 7.

COSSU, F., A. MORO, and M. RENDALL, “Training time, robots and technological unemployment”, *CEPR Discussion Papers No. 19343* (2024). 7.

CROUZET, N., J. C. EBERLY, A. L. EISFELDT, and D. PAPANIKOLAOU, “The economics of intangible capital”, *Journal of Economic Perspectives*, vol. 36, no. 3 (2022), pp. 29-52. 10.

CULLEN, D. E., “The interindustry wage structure, 1899-1950”, *American Economic Review*, vol. 46, no. 3 (1956), pp. 353-369. 6.

DAVIDSON, C. and M. REICH, “Income inequality: an inter-industry analysis”, *Industrial Relations*, vol. 27, no. 3 (1988), pp. 263-286. 7.

DAVIS, S. and J. HALTIWANGER, “Wage dispersion between and within U.S. manufacturing plants”, *Brookings Papers on Economic Activity* (1991). 6.

DICKENS, W. and L. KATZ, *Interindustry wage differences and industry characteristics*, IN: *Unemployment and the Structure of Labor Markets*, pp. 48-89, edited by Kevin Lang and Jonathan Shawn Leonard, London: Basil Blackwell 1987. 6.

DODINI, S., K. G. SALVANES, and A. WILLÉN, “The dynamics of power in labor markets: monopolistic unions versus monopsonistic employers”, *CESifo Working Paper No. 9495* (2021). 40.

DUNNE, T., L. FOSTER, J. HALTIWANGER, and K. R. TROSKE, “Wage and productivity dispersion in United States manufacturing: the role of computer investment”, *Journal of Labor Economics*, vol. 22, no. 2 (2004), pp. 397-429. 6.

EDEN, M. and P. GAGGL, “On the welfare implications of automation”, *Review of Economic Dynamics*, vol. 19 (2018), pp. 15-43. 8.

EECKHOUT, J., *The Profit Paradox: how thriving firms threaten the future of work*, Princeton University Press, Princeton, New Jersey 2021. 6.

EPI, “Wage inequality fell in 2023 amid a strong labor market, bucking long-term trends”, *Working Economics Blog by Elise Gould and Jori Kandra, Economic Policy Institute* (2024). 2.

EPIFANI, P. and G. GANCIA, “The skill bias of world trade”, *The Economic Journal*, vol. 118, no. 530 (2008), pp. 927-960. 2.

EROSA, A., L. FUSTER, G. KAMBOUROV, and R. ROGERSON, “Labor market polarization and inequality: a Roy model perspective”, *NBER Working Paper No. 33687* (2025). 7.

FED, “Wage inequality across the U.S.” *Regional Spotlight by Kevin Curran, Federal Reserve Bank of Philadelphia*, no. Q2 (2024). 2.

FIELDS, J. and E. N. WOLFF, "Interindustry wage differentials and the gender wage gap", *Industrial and Labor Relations Review*, vol. 49, no. 1 (1995), pp. 105-120. 6.

FILIPPI, E., M. BANNÒ, and S. TRENTO, "Automation technologies and their impact on employment: a review, synthesis and future research agenda", *Technological Forecasting & Social Change*, vol. 191 (2023), pp. 122-448. 32.

FREUND, L., "Superstar teams: the micro origins and macro implications of coworker complementarities", *Job Market Paper* (2024). 7.

GENRE, V., K. KOHN, and D. MOMFERATOU, "Understanding inter-industry wage structures in the euro area", *Applied Economics*, vol. 43, no. 11 (2011), pp. 1299-1313. 7.

GENRE, V., D. MOMFERATOU, and G. MOURRE, "Wage diversity in the euro area - an overview of labour cost differentials across industries", *ECB Occasional Paper No. 24/2005* (2005). 7.

GIBBONS, R. and L. KATZ, "Does unmeasured ability explain inter-industry wage differentials?", *Review of Economic Studies*, vol. 59, no. 3 (1992), pp. 515-535. 7.

GIBBONS, R., L. KATZ, T. LEMIEUX, and D. PARENT, "Comparative advantage, learning and sectoral wage determination", *Journal of Labor Economics*, vol. 23, no. 4 (2005), pp. 681-724. 7, 19.

GITTLEMAN, M. and E. N. WOLFF, "International comparison of inter-industry wage differentials", *Review of Income and Wealth*, vol. 39, no. 3 (1993), pp. 295-312. 7.

GLOVER, A. and J. SHORT, "Demographic origins of the decline in labor's share", *Staff Working Paper, Bank of Canada* (2023). 8.

GOOS, M. and A. MANNING, "Lousy and lovely jobs: the rising polarization of work in Britain", *Review of Economics and Statistics*, vol. 89, no. 1 (2007), pp. 118-133. 7.

GOOS, M., A. MANNING, and A. SALOMONS, "Job polarization in Europe", *American Economic Association: Papers and Proceedings*, vol. 99, no. 2 (2009), pp. 58-63. 7.

GROSHEN, E. L., "Sources of intra-industry wage dispersion: how much do employers matter?", *Quarterly Journal of Economics*, vol. 106, no. 3 (1991), pp. 869-884. 6.

HÅKANSON, C., E. LINDQVIST, and J. VLACHOS, "Firms and skills: the evolution of worker sorting", *Journal of Human Resources*, vol. 56, no. 2 (2020), pp. 512-538. 19.

HALTIWANGER, J., H. HYATT, and J. SPLETZER, "Increasing earnings inequality: reconciling evidence from survey and administrative data", *Journal of Labor Economics*, vol. 41, no. S1 (2023), pp. S61-S93. 7, 19.

— "Rising top, falling bottom: industries and rising wage inequality", *American Economic Review*, vol. 114, no. 10 (2024), pp. 3250-3283. 2, 7, 12, 15, 16, 19.

HECKMAN, J. J. and G. SEDLACEK, "Heterogeneity, aggregation, and market wage functions: an empirical model of self-selection in the labor market", *Journal of Political Economy*, vol. 93, no. 6 (1985), pp. 1077-1125. 18.

HERRENDORF, B., C. HERRINGTON, and Á. VALENTINYI, "Sectoral technology and structural transformation", *American Economic Journal: Macroeconomics*, vol. 7, no. 4 (2015), pp. 104-133. 8, 30.

HERRENDORF, B., R. ROGERSON, and Á. VALENTINYI, "Growth and structural transformation", IN: *Handbook of Economic Growth*, vol. 2, pp. 855-941, edited by Philippe Aghion and Steven N. Durlauf, Amsterdam: North Holland 2014. 8.

HICKS, J. R., *The theory of wages*, Palgrave Macmillan, London 1932. 20, 43.

HOFFMANN, F., D. S. LEE, and T. LEMIEUX, "Growing income inequality in the United States and other advanced economies", *Journal of Economic Perspectives*, vol. 34, no. 4 (2020), pp. 52-78. 7.

HONG, G., "Two-sided sorting of workers and firms: implications for spatial inequality and welfare", *Job Market Paper* (2024). 7.

HOROWITZ, M. A. and I. L. HERRNSTADT, "Changes in the skill requirements of occupations in selected industries", IN: *The Employment Impact of Technological Change*, pp. 223-287, edited by National Commission on Technology, Automation, and Economic Progress, Washington, D.C.: G.P.O. 1966. 11.

HORVATH, M., "Sectoral shocks and aggregate fluctuations", *Journal of Monetary Economics*, vol. 45, no. 1 (2000), pp. 69-106. 20.

HOWELL, D. R. and E. N. WOLFF, "Skills, bargaining power and rising interindustry wage inequality since 1970", *Review of Radical Political Economics*, vol. 23, no. 1-2 (1991), pp. 30-37. 7.

HSIEH, C.-T., E. HURST, C. I. JONES, and P. J. KLENOW, "The allocation of talent and U.S. economic growth", *Econometrica*, vol. 87, no. 5 (2019), pp. 1439-1474. 18.

JAIMOVICH, N. and H. E. SIU, "Job polarization and jobless recoveries", *Review of Economics and Statistics*, vol. 102, no. 1 (2020), pp. 129-147. 7.

JAIMOVICH, N., M. B. ZHANG, and N. VINCENT, "Under the hood of the routine share decline", *Economic Letters*, vol. 234 (2024), p. 111437. 7.

KARABARBOUNIS, L., "Perspectives on the labor share", *Journal of Economic Perspectives*, vol. 38, no. 2 (2024), pp. 107-136. 8.

KARABARBOUNIS, L. and B. NEIMAN, "The global decline of the labor share", *Quarterly Journal of Economics*, vol. 29, no. 1 (2014), pp. 61-103. 4, 8, 18, 28-30.

KATZ, L. and D. AUTOR, "Changes in the wage structure and earnings inequality", IN: *Handbook of Labor Economics*, vol. 3A, pp. 1463-1555, edited by Orley C. Ashenfelter and David Card, Amsterdam: North Holland 1999. 6.

KATZ, L. and K. MURPHY, "Changes in relative wages, 1963-1987: supply and demand factors", *Quarterly Journal of Economics*, vol. 70, no. 1 (1992), pp. 35-78. 3, 7.

KLEINMANN, B., "Wage inequality and the spatial expansion of firms", *Job Market Paper* (2023). 7, 15.

KLUMP, R., P. MCADAM, and A. WILLMAN, “Factor substitution and factor-augmenting technical progress in the United States: a normalized supply-side system approach”, *Review of Economics and Statistics*, vol. 89, no. 1 (2007), pp. 183-192. 30.

KRUEGER, A. and L. SUMMERS, “Reflections on the inter-industry wage structure”, IN: *Unemployment and the Structure of Labor Markets*, edited by Kevin Lang and Jonathan Shawn Leonard, London: Basil Blackwell 1987. 6.

— “Efficiency wages and the inter-industry wage structure”, *Econometrica*, vol. 56, no. 2 (1988), pp. 259-293. 6, 7.

KRUSELL, P., L. E. OHANIAN, J.-V. RÍOS-RULL, and G. L. VIOLANTE, “Capital-skill complementarity and inequality: a macroeconomic analysis”, *Econometrica*, vol. 68, no. 5 (2000), pp. 1029-1053. 4, 8, 22, 23.

LEMIEUX, T., “What do we really know about changes in wage inequality?”, IN: *Labor in the New Economy*, pp. 17-62, edited by Katharine G. Abraham, James R. Spletzer, and Michael Harper, National Bureau of Economic Research: Studies in Income and Wealth,The University of Chicago Press 2010. 6.

LEÓN-LEDESMA, M. and A. MORO, “The rise of services and balanced growth in theory and data”, *American Economic Journal: Macroeconomics*, vol. 12, no. 4 (2020), pp. 109-146. 16.

LEONARDI, M., “Firm heterogeneity in capital-labour ratios and wage inequality”, *The Economic Journal*, vol. 117, no. 518 (2007), pp. 375-398. 6.

MACERA, M. and H. TSUJIYAMA, “Inequality and technological change”, *Quantitative Economics*, vol. 15, no. 2 (2024), pp. 427-451. 7.

MANNING, A., “Monopsony in labor markets: a review”, *International Economic Review*, vol. 74, no. 1 (2021), pp. 3-26. 4, 19.

MASSENKOFF, M. and N. WILMERS, “Wage stagnation and the decline of standardized pay rates, 1974-1991”, *American Economic Journal: Applied Economics*, vol. 15, no. 1 (2023), pp. 474-507. 33.

MATSUYAMA, K., “Structural change in an interdependent world: a global view of manufacturing decline”, *Journal of the European Economic Association*, vol. 7, no. 2-3 (2009), pp. 478-486. 8.

MC FADDEN, D., “Conditional logit analysis of qualitative choice behavior”, IN: *Frontiers of Econometrics*, pp. 105-142, edited by Paul Zarembka, New York 1974. 24.

— “A Method of Simulated Moments for estimation of discrete response models without numerical integration”, *Econometrica*, vol. 57, no. 5 (1989), pp. 995-1026. 28, 31.

MELMAN, S., “The rise of administrative overhead in the manufacturing industries of the United States 1899-1947”, *Oxford Economic Papers*, vol. 3, no. 1 (1951), pp. 62-112. 11.

MICHAELS, G., A. NATRAJ, and J. V. REENEN, “Has ICT polarized skill demand? Evidence from eleven countries over twenty-five years”, *Review of Economics and Statistics*, vol. 96, no. 1 (2014), pp. 60-77. 2.

Montgomery, J. D., "Equilibrium wage dispersion and interindustry wage differentials", *Quarterly Journal of Economics*, vol. 106, no. 1 (1991), pp. 163-179. 6.

Moro, A., "The structural transformation between manufacturing and services and the decline in the US GDP volatility", *Review of Economic Dynamics*, vol. 15, no. 3 (2012), pp. 402-415. 16.

Ngai, R. L. and C. A. Pissarides, "Structural change in a multisector model of growth", *American Economic Review*, vol. 97, no. 1 (2007), pp. 429-443. 17.

Oberfield, E. and D. Raval, "Micro data and macro technology", *Econometrica*, vol. 89, no. 2 (2021), pp. 703-732. 30.

Ohanian, L. E., M. Orak, and S. Shen, "Revisiting capital-skill complementarity, inequality, and labor share", *Review of Economic Dynamics*, vol. 51 (2023), pp. 479-505. 8.

Piketty, T., *Le Capital au XXIe siècle*, Éditions du Seuil, Seuil, 25 boulevard Romain-Rolland, Paris 14 2013. 30.

Prager, E. and M. Schmitt, "Employer consolidation and wages: evidence from hospitals", *American Economic Review*, vol. 11, no. 2 (2021), pp. 397-427. 40.

Ray, D., "Uneven growth: a framework for research in development economics", *Journal of Economic Perspectives*, vol. 24, no. 3 (2010), pp. 45-60. 8.

Rogerson, R., "Why labor supply matters for macroeconomics", *Journal of Economic Perspectives*, vol. 38, no. 2 (2024), pp. 137-158. 18.

Roy, A. D., "Some thoughts on the distribution of earnings", *Oxford Economic Papers*, vol. 3, no. 2 (1951), pp. 135-146. 18.

Rumberger, R. W., "The changing skill requirements of jobs in the U.S. economy", *Industrial and Labor Relations Review*, vol. 34, no. 4 (1981), pp. 578-590. 11.

Siena, D. and R. Zago, "Job polarisation, labour market fluidity and the flattening of the Phillips curve", *The Economic Journal*, vol. 134, no. 661 (2024), pp. 2141-2174. 7.

Slichter, S. H., "Notes on the structure of wages", *Review of Economics and Statistics*, vol. 32, no. 1 (1950), pp. 80-91. 6.

Song, J., D. J. Price, F. Guvenen, N. Bloom, and T. von Wachter, "Firming up inequality", *Quarterly Journal of Economics*, vol. 134, no. 1 (2019), pp. 1-50. 6, 19.

Thaler, R. H., "Anomalies: interindustry wage differentials", *Journal of Economic Perspectives*, vol. 3, no. 2 (1989), pp. 181-193. 6.

Tinbergen, J., "Substitution of gradute by other labour", *Kylos*, vol. 27, no. 2 (1974), pp. 217-226. 3.

Vollrath, D., "The elasticity of aggregate output with respect to capital and labor", *American Economic Journal: Macroeconomics*, vol. 16, no. 4 (2024), pp. 470-504. 28.

Yeh, C., C. Macaluso, and B. Hershbein, "Monopsony in the U.S. labor market", *American Economic Review*, vol. 112, no. 7 (2022), pp. 2099-2138. 32.

Online Appendix

(Outline) *In this appendix I report all the material complementary to the main text; it is made of additional tables and figures, and of discussions on further analytical results. Section A complements and enriches the exposition of the empirical findings in Section 1; Section B derives all the salient elements of the structural general equilibrium model outlined in Section 2, while Section C consolidates and further discusses the calibration strategy and the counterfactual analysis of the model of Sections 3-4. A replication is in Section D under both monopsony and monopolistically competitive power of firms. Section E studies qualitatively the differences across industries in terms of employment fluctuations. Finally, Section F shows some facts on capital stocks, labour force composition and real wages for 2-digit US 2017 NAICS industries. Part of this appendix is not intended for publication purposes.*

A. Motivating evidence: data, figures and tables

(Data details) *Data are for United States (US). For what concerns data from Bureau of Economic Analysis (BEA), private non-residential capital types are in net stocks evaluated at current costs by detailed industry dating back from 1925 to 2022.*[I] *Gross categories are "total equipment", "total structures", and "total intellectual property products", and each contains different types of assets according to their own National Income and Product Accounts (NIPA) asset type code; in total there are 96 different asset types. Data are provided for 74 industries at different layers.*[II] *Among all these types of capital assets I am going to classify them accordingly: digital equipment is made of "Mainframes", "PCs", "DASDs", "Printers", "Terminals", "Tape Drives", "Storage Devices", and "System Integrators"; the stock of intangible capital coincides with that of "Total Intellectual Property Products" (IPP);*[III] *while physical (or non-ICT) capital is the sum of all the remaining asset types.*[IV] *I extract also annual data on (seasonally adjusted) value added, wages and salaries, and of persons engaged in production (effective workforce) for each industry. To complement these data, annual (seasonally adjusted) Consumer Pirce Index (CPI) for all items (indexed at 2015 =*

[I] Starting year is 1998 so that industries are classified with the latest available system, the US 2017 NAICS; before, classification follows the US Standard Industrial Classification (SIC) system. Assets' value is expressed in millions of US dollars, and last update was in November 3, 2023.

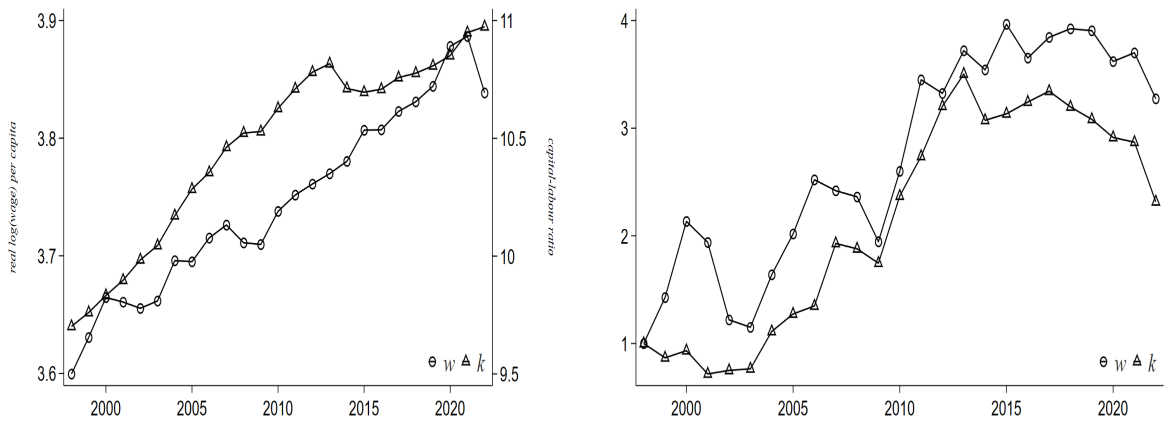
[II] Classified according the BEA industry code system. Most are classified at 3-digit US 2017 NAICS level (some 3-digit industries may fall in the same BEA code), four at 2-digit ("construction", "management of companies and enterprises", "educational services", and "other services, except government"), while five industries related to finance and insurance are at 4-digit level.

[III] A recent discussion analyses how the BEA collects data on IPP. Koh et al. (2020) argue that the effects of IPP capital on the US labour share only emerged since 2013, when the BEA revised its methodology by reclassifying the notion of capital; now, the capital income comprises the rents arising from IPP investment. The authors compare the IPP effect on the labour share using both pre- and post-2013 data, finding out a negative effect of the rise in IPP on the US labour share.

[IV] Similar classification in Arvai and Mann (2022), as well coherent with Eden and Gaggl (2018).

100) is taken from Federal Reserve Economic Data (FRED) database.

Regarding the data extracted from Bureau of Labor Statistics (BLS), information are available for a total of more than 80 industries at 3-digit US 2017 NAICS level starting from 2003.[V] *At workers' level, each industry displays information on a set of several occupations classified according to the U.S. Office of Management and Budget's Standard Occupational Classification (SOC) system, i.e., occupations are categorized based on the type of job and on required skills, and employees are assigned to an occupation based on the work they perform and not on their education or training. For my purposes I classify occupations by considering their "major" group membership:*[VI] *I divide such major occupations in both routine and non-routine tasks. The latter group considers occupations such as "Management", "Business and Financial Operations", "Computer and Mathematical", "Architecture and Engineering", "Life, Physical, and Social Science", "Community and Social Service", "Legal", "Educational Training and Library", and "Arts, Design, Entertainment, Sports, and Media", while the left-outside occupations are comprised in the group of routine worker tasks.*



(A) LEVELS

(B) STANDARD DEVIATIONS

FIGURE A.1: CAPITAL AND WAGE SERIES

Note: this figure depicts the evolution of capital and real wages, all taken in per capita *log*-terms, across industries. Panel (a) plots the evolution of series in levels, while Panel (b) plots the associated dispersion measured in standard deviation; series are standardized and indexed to 1 in 1998, so that both y-axis indexes the respective measure given the initial value at unity. Plots are referred to 3-digit US 2017 NAICS industries. *Source*: BEA and own calculations.

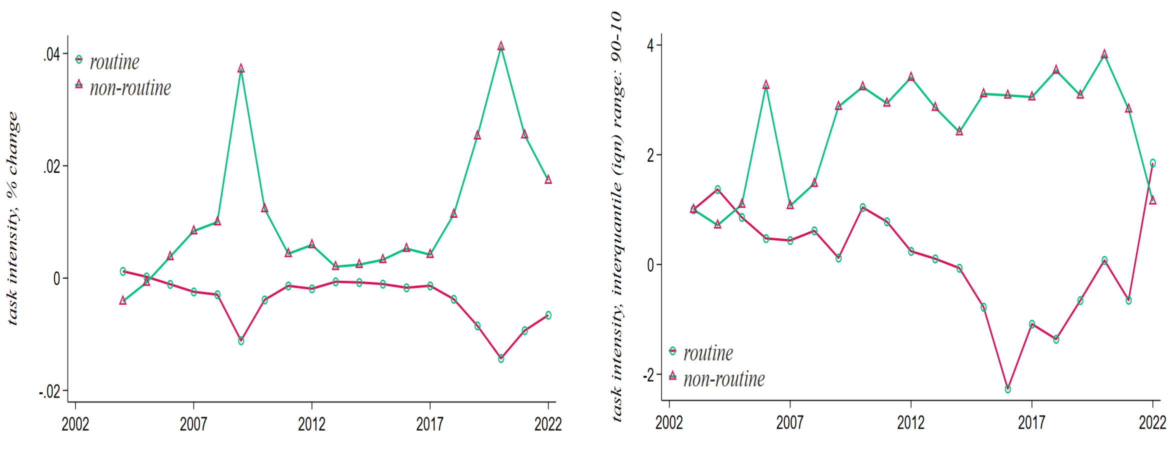
[V] The number of industries is variable year by year due to issues of data sampling. Moreover, prior 2003, these are classified according to the Standard Industrial Classification (SIC) system.

[VI] This choice arises from the fact that there are missing group definitions for some more detailed occupations. In fact, the number of occupations in each industry is not fixed: there are from 80 to 180 types of occupations for each industry, and these are clustered in common 22 major groups.

TABLE A.1: REGRESSIONS, CAPITAL STOCKS

	$log(w(s))$			
	(1)	(2)	(3)	(4)
$\beta_{k^{phy}}$	.134***	.122**	.164***	.114***
	(3.48)	(2.94)	(9.05)	(3.52)
$\beta_{k^{ict}}$	.052*			.049*
	(2.00)			(2.27)
$\beta_{k^{int}}$		.057*		
		(2.03)		
$\beta_{k^{deq}}$		-.003		
		(-.26)		
$\beta_{k^{int}} \times \beta_{k^{deq}}$			.009**	.009**
			(2.99)	(2.80)
R^2	.461	.491	.287	.497

*t-statistics in parentheses. * (p<0.05), ** (p<0.01), *** (p<0.001). Analysis at 3/4-digit US 2017 NAICS industries over 1998-2022 on* N = 1650 *observations. The Fixed Effects (Fe) regressions are of the form* $y\left(log\left(w_t(s)\right) \mid \mathcal{X}_{i,t}\right) = \beta_c + \beta_i \mathcal{X}_{i,t} + u_t$*, with* $\mathcal{X}_i$ *representing the different capital-labour ratios considered. Results are robust even by controlling for the log size of the industries, or even taking capital series directly in levels. Variables are all in* log *format. Constant not reported to save space. Source: BEA and own calculations.*



(A) CHANGES

(B) INTERQUARTILE RANGE, 90^{th}-10^{th}

FIGURE A.2: TASK INTENSITY

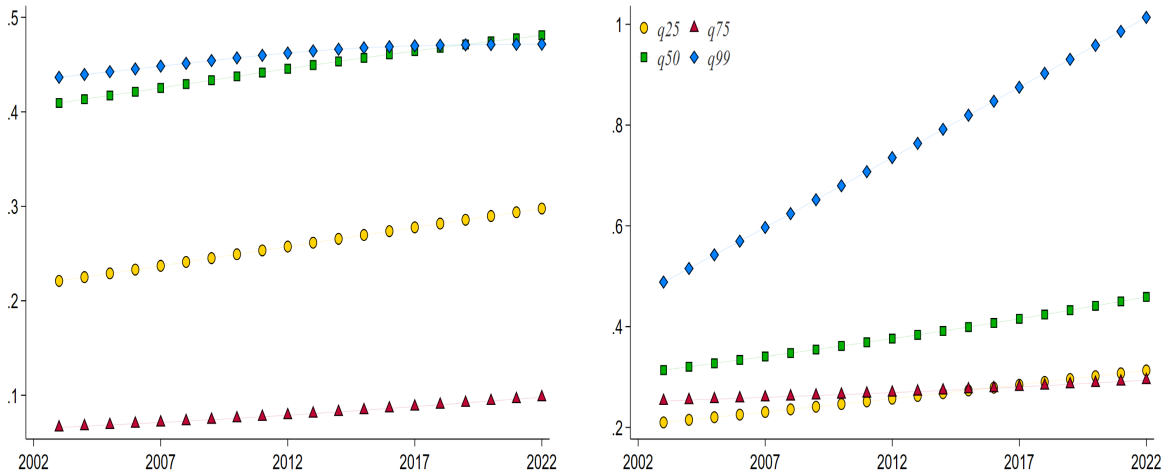
Note: these figures plot the evolution of task intensity (namely the share of each task in the total employment) of both routine (red) and non-routine (green) workers. Panel (a) depicts the year-by-year percentage cahnge in both series, while Panel (b) plots the yearly difference between top and bottom 10% of each component. Series are standardized and indexed to 1 in 1998, so that both y-axis indexes the respective measure given the initial value at unity. Plots are referred to 3-digit US 2017 NAICS industries. *Source*: BLS and own calculations.

(A) ROUTINE WORKERS

(B) NON-ROUTINE WORKERS

FIGURE A.3: LABOUR SHARES PATTERN

Note: this figure shows the fitted values and the associated linear trend for the labour share of both routine and non-routine workers. The fitted values are extracted from a Fixed Effects (Fe) regression for both the labour share measures with year and industry fixed effects. *Source*: BLS and own calculations.



(A) ICT CAPITAL RATIO

(B) TASK RATIO

FIGURE A.4: CHANGES BY PERCENTILES

Note: each subplot draws the HP-filtered trend in ICT capital ratio (ICT capital stock in physical capital quantity), and in task ratio (fraction of non-routine workers of routine ones), respectively. Series are divided according the growth in group-specific industry wage (*i.e.*, total $\Delta_{\%}$ in industry wage per worker). Industries are classified at 3-digit US 2017 NAICS level. *Source*: BEA, BLS and own calculations.

TABLE A.2: COMBINED REGRESSIONS, PERCENTAGE CHANGES

	$\Delta\, log(w(s))$		
	(1)	(2)	(3)
$\beta_{\Delta k}$	.054***		.009
	(.002)		(.008)
$\beta_{\Delta \ell}$	.035*		.035***
	(.018)		(.007)
$\beta_{\Delta k \times \Delta \ell}$		.982	.919***
		(.649)	(.152)
R^2	.030	.021	.037
N	1178	1178	1178

*t-statistics in parentheses. * (p<0.05), ** (p<0.01), *** (p<0.001). Analysis at 3-digit US 2017 NAICS industries over 2003-2022. The Fixed Effects (Fe) regressions are of the form* $y\left(\Delta\, log\left(w_t(s)\right) \mid \mathcal{X}_{i,t}\,,\, \mathcal{Z}_j\right) = \beta_c + \beta_i \mathcal{X}_{i,t} + \delta_j \mathcal{Z}_{j,t} + u_t$*, with* $\mathcal{X}_i$ *representing the percentage change in both ICT-to-physical capital and non-routine-over-routine workers ratios, and* $\mathcal{Z}_j$ *being a set of time-varying controls. Variables are all in* log *format. Constant not reported to save space.* Source: *BEA, BLS and own calculations.*

TABLE A.3: COMBINED REGRESSIONS BY GROUPS, PERCENTAGE CHANGES

	$\Delta\, log(w(s))$			
	0-25 quantile	*25-50 quantile*	*50-75 quantile*	*75-100 quantile*
$\beta_{\Delta k}$	-.693	.302***	.078	-.082*
	(.618)	(.072)	(.179)	(.042)
$\beta_{\Delta \ell}$	.041***	-.297	.015***	.052*
	(.004)	(.247)	(.003)	(.025)
$\beta_{\Delta k \times \Delta \ell}$	.876***	-1.304	-.643	1.560*
	(.100)	(2.945)	(.470)	(.789)

*Significance level at * (p<0.05), ** (p<0.01), *** (p<0.001). Standard error in parentheses. Analysis at 3-digit US 2017 NAICS industries in 2003-2022. Each Fixed Effects (Fe) regression – performed on groups of industries clustered in quantiles* (ω) *according to their overall growth in real wage – , is of the form* $y_\omega\left(\Delta\, log\left(w_t(s)\right) \mid \mathcal{X}_{i,\omega t}, \mathcal{Z}_{j,\omega t}\right) = \beta_{c,\omega} + \beta_{i,\omega} \mathcal{X}_{i,\omega t} + \delta_{j,\omega} \mathcal{Z}_{j,\omega t} + u_{\omega t}$*, with* $\mathcal{X}_i$ *representing the percentage change in both ICT-to-physical capital and non-routine-over-routine workers ratios, and* $\mathcal{Z}_j$ *being a set of time-varying controls. Variables are all in* log *format. Constant not reported to save space.* Source: *BEA, BLS and own calculations.*

Table A.4: Combined regressions, levels

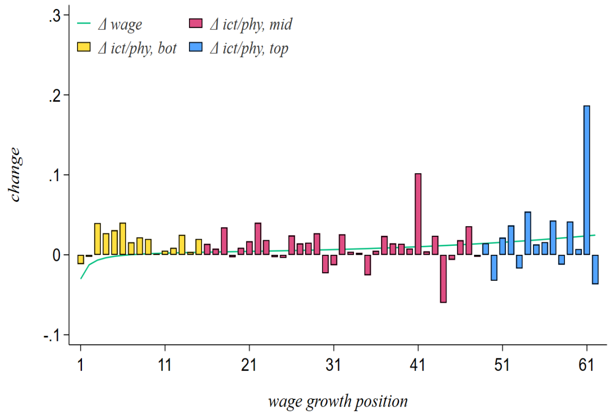
	$log(w(s))$				
	Fe	*25th quantile*	*50th quantile*	*75th quantile*	*100th quantile*
β_k	.102**	.084***	.102***	.119***	.171*
	(.040)	(.029)	(.022)	(.027)	(.074)
β_ℓ	.299***	.269***	.300***	.328***	.416***
	(.078)	(.040)	(.030)	(.037)	(.104)
$\beta_{k\times\ell}$	.031	.029***	.031***	.034***	.041
	(1.89)	(.010)	(.008)	(.009)	(.025)

*Significance level at * (p<0.05), ** (p<0.01), *** (p<0.001). Standard error in parentheses. Analysis at 3-digit US 2017 NAICS industries in 2003-2022 on* $N = 1240$ *observations. The Fixed Effects (Fe) regression is of the form* $y\left(log\left(w_t(s)\right) \mid \mathcal{X}_{i,t}, \mathcal{Z}_{j,t}\right) = \beta_c + \beta_i \mathcal{X}_{i,t} + \delta_j \mathcal{Z}_{j,t} + u_t$, *with* $i = k, \ell$, *and* $\mathcal{Z}_j$ *being a set of controls, and it has associated* $R^2 = .348$. *Analogously, the conditional quantile regressions are then* $\mathcal{Q}_\omega\left(log\left(w_t(s)\right) \mid \mathcal{X}_{i,\omega t}, \mathcal{Z}_{j,\omega t}\right) = \beta_{i,\omega}\mathcal{X}_{i,\omega t} + \delta_{j,\omega}\mathcal{Z}_{j,\omega t} + u_{\omega t}$, *where* ω *represents each quantile (defined on the independent variable). Variables are all in* log *format. Constant not reported to save space, while quantile regressions do not have the constant term. Source: BEA, BLS and own calculations.*

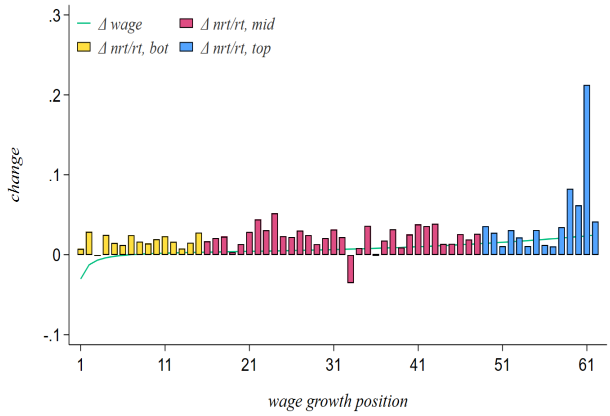
Table A.5: Combined regressions, standard deviations

	$sd\left[log(w(s))\right]$				R^2	
	(1)		(2)			
	$\beta_{sd(k)}$	β_ℓ	β_k	$\beta_{sd(\ell)}$	(1)	(2)
25th quantile	.256***	.070***	.008***	.403***		
	(.054)	(.015)	(.002)	(.010)		
50th quantile	.121***	.051***	.008***	.404***		
	(.034)	(.009)	(.002)	(.008)		
75th quantile	.031	.038***	.008***	.405***		
	(.039)	(.011)	(.002)	(.010)		
100th quantile	-.127	.015	.008	.408***		
	(.112)	(.024)	(.005)	(.021)		
Fe	.149***	.055***	.008***	.404***	.324	.793
	(.031)	(.010)	(.002)	(.007)		

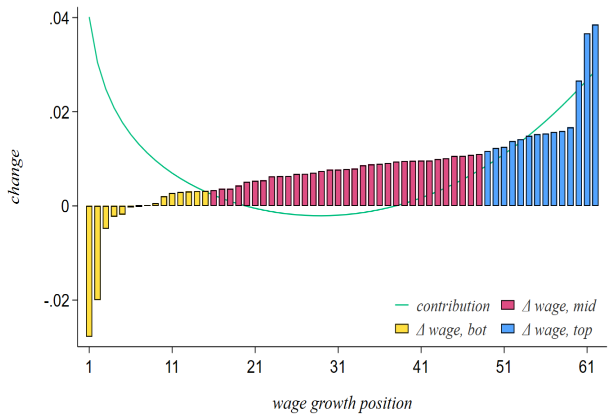
*Significance level at * (p<0.05), ** (p<0.01), *** (p<0.001). Standard error in parentheses. Analysis at 3-digit US 2017 NAICS industries in 2003-2022 on* $N = 1240$ *observations. The Fixed Effects (Fe) regression is of the form* $y\left(log\left(w_t(s)\right) \mid \mathcal{X}_{i,t}, \mathcal{Z}_{j,t}\right) = \beta_c + \beta_i \mathcal{X}_{i,t} + \delta_j \mathcal{Z}_{j,t} + u_t$, *with* $i = k, \ell$, *and* $\mathcal{Z}_j$ *being a set of controls. Analogously, the conditional quantile regressions are then* $\mathcal{Q}_\omega\left(log\left(w_t(s)\right) \mid \mathcal{X}_{i,\omega t}, \mathcal{Z}_{j,\omega t}\right) = \beta_{i,\omega}\mathcal{X}_{i,\omega t} + \delta_{j,\omega}\mathcal{Z}_{j,\omega t} + u_{\omega t}$, *where* ω *represents each quantile (defined on the independent variable). Variables are all in* log *or* sd *format Constant not reported to save space, while quantile regressions do not have the constant term. Source: BEA, BLS and own calculations.*



(A) ICT RATIO



(B) TASK RATIO



(C) VARIANCE CONTRIBUTION

FIGURE A.5: CHANGES ACROSS THE WAGE GROWTH DISTRIBUTION

Note: this figure represents the changing behaviour of given series across the industry-level real *log*-wage growth distribution over the period 2003-2022. Panel (a) depicts the ICT-to-non-ICT capital ratio, panel (b) the non-routine over routine tasks ratio, and panel (c) shows the contribution of each industry to between-industry wage inequality. Bars refer to the industry wage growth, and they are coloured as follows: *(i)* bottom 25% industries are identified with yellow, *(ii)* middle 50% are those in red, while *(iii)* top 25% industries are coloured in blue. *Source*: BEA, BLS and own calculations.

(Group decomposition) *Total change in wage inequality can be written also as*

$$
\begin{aligned}
\underbrace{\Delta\,\widetilde{var}\Big(w_t(s)-\overline{w}_t\Big)}_{\textit{total, wages}} = {} & \underbrace{\left(\frac{\ell_0(g)}{\ell_0}\right)\left[\Delta\,\widetilde{var}\Big(w_t(s\in g)-\overline{w}_t(g)\Big)\right]}_{\textit{within-group, wages}} \\
& + \underbrace{\sum_g \left[\Delta\,\widetilde{var}\Big(\ell_t(s)-\overline{\ell}_t(g)\Big)\right]\widetilde{var}\Big(w_0(s)-\overline{w}_0(g)\Big)}_{\textit{between-groups, employment}} \\
& + \underbrace{\sum_g \left[\Delta\,\widetilde{var}\Big(w_t(s)-\overline{w}_t(g)\Big)\right]\left[\Delta\,\widetilde{var}\Big(\ell_t(s)-\overline{\ell}_t(g)\Big)\right]}_{\textit{between-groups, interaction}} \\
& + \underbrace{\underbrace{\sum_{\mathcal{G}/g}\left(\frac{\ell_0\left(\mathcal{G}\right)}{\ell_0}\right)\left[\Delta\,\widetilde{var}\Big(w_t(s)-\overline{w}_t\left(\mathcal{G}\right)\Big)\right]}_{\textit{within-other groups, wages}}
+ \underbrace{\sum_g \left[\Delta\left(\frac{\ell_t(g)}{\ell_t}\right)\widetilde{var}\Big(\overline{w}_t(g)-\overline{w}_t\Big)\right]}_{\textit{between groups, wages}}}_{\textit{residual}}
\end{aligned}
\qquad \textbf{(A.1)}
$$

where industries are partitioned in $g \in \mathcal{G}$ groups, and variances are employment-weighted. Subscript $t = 0$ indicates the initial level (starting year of the sample). Total change in variance can be decomposed in several components: (i) rise in variance for a particular group g; (ii) reallocation of employment across groups, keeping constant the variance of each group at its base level; (iii) cross-changes of wages and employment; (iv) rising variance within all other groups but g; and (v) rising variance between groups. Quantification of each component is in Table A.6; this decomposition is borrowed from Kleinmann (2023).

TABLE A.6: DECOMPOSITION OF THE RISE IN WAGE INEQUALITY

	***industry group** g*				
share of the increase, wage variance	(1) *tails*	(2) *middle*	(3) *services*	(4) *manuf.*	(5) *other*
rising variance within the group	79%	32%	58%	11%	27%
employment reallocation across groups	34%	34%	17%	51%	10%
comovement (variance, employment)	7%	7%	3%	4%	5%
residual	-20%	27%	-22%	-34%	58%
total change across all industries	*100%*	*100%*	*100%*	*100%*	*100%*

Estimates of each component in eq. (A.1) for US 3-digit US 2017 NAICS industries between 2003 and 2022 related to $\log(w(s))$. *Operator* Δ *in the equation is* $x_t - x_{t-1}$, *and not a percentage change. The first row shows the share of total increase in variance due to rising variance in the group of industries; the second row shows the share due to changes in employment between that group and the other industries in the sample (employment reallocation), holding constant the change in variance in each group; the third row shows the share that is due to the cross-product of rising variance and rising employment share; the fourth row is so that the sum for each column is 100%. "tails" and "middle" are referred to overall percentage changes distribution in industry real wage per capita; "manuf." stands for manufacturing industries, while "other" does not consider services and manufacturing industries. Source: BEA and own calculations.*

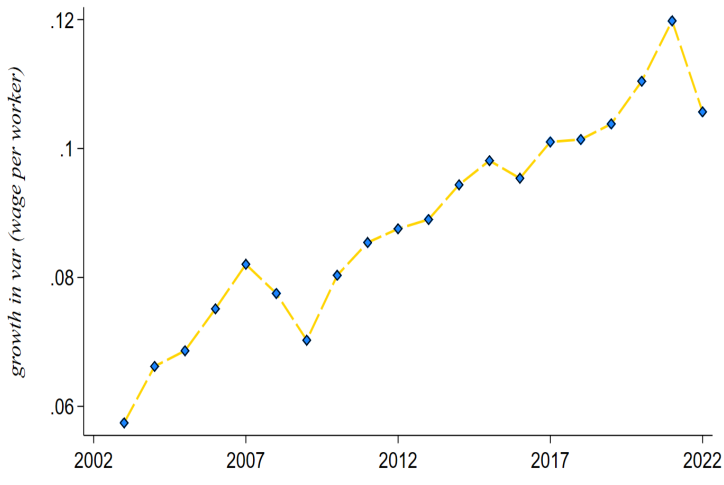


FIGURE A.6: BETWEEN-INDUSTRY WAGE VARIANCE GROWTH

Note: this figure plots the evolution of between-industry variance growth as defined in eq. (2). Plot is referred to 3-digit US 2017 NAICS industries. *Source*: BEA and own calculations.

TABLE A.7: INDUSTRY CONTRIBUTION TO WAGE VARIANCE GROWTH

industry	***contribution share*** (%)	***group***
Administrative and Support Services	0.01	*top*
Agriculture	0.12	*top*
Ambulatory Health Care Services	0.23	*bottom*
Amusement, Gambling, and Recreation industries	0.62	*bottom*
Chemical Manufacturing	-0.26	*bottom*
Computer and Electronic Product Manufacturing	0.94	*top*
Fabricated Metal Product Manufacturing	0.14	*bottom*
Federal Reserve banks, Credit Intermediation, and related activities	0.47	*top*
Food Services and Drinking Places	2.36	*top*
Food and Beverage Stores	1.34	*bottom*
Food and Beverage and Tobacco Products	0.39	*bottom*
Funds, Trusts, and Other Financial Vehicles	0.10	*top*
General Merchandise Stores	1.29	*bottom*
Information and Data Processing Services	5.90	*top*
Machinery Manufacturing	-0.02	*bottom*
Management of Companies and Enterprises	2.71	*top*
Oil and Gas Extraction	0.26	*top*
Other Services, except government	0.43	*top*
Other Transportation and Support Activities	0.67	*bottom*
Paper Manufacturing	-0.02	*bottom*
Performing Arts, Spectator Sports, Museums, and related activities	-0.02	*top*
Printing and Related Support Activities	0.08	*bottom*
Professional, Scientific, and Technical Services	11.7	*bottom*
Publishing industries (including software)	2.23	*top*
Rail Transportation	-0.10	*bottom*
Real Estate	-0.04	*top*
Rental and Leasing Services and Lessors of Intangible Assets	-0.08	*top*
Securities, Commodity Contracts, and Other Financial Investments and Related Activities	8.59	*top*
Transportation Equipment Manufacturing	1.17	*bottom*
Warehousing and Storage	0.86	*bottom*

Contribution to between-industry wage variance growth of industries comprised in top and bottom (in terms of overall growth in real log*-wage per capita, as reported by Table 2) groups over the period 2003-2022. Variance contribution follows the definition proposed in eq. (2). Industries are at US 3-digit US 2017 NAICS level.* Source: *BEA and own calculations.*

B. Model derivation

(Household inter-temporal problem) *The household utility problem in eq. (4) can be rewritten inter-temporally, future-discounted by factor β, as*

$$\max_{\mathcal{C}_t^i,\ b_{t+1}^i,\ \{k_{t+1}^i(j)\}_{\forall j}} \mathcal{U}_{h,t}^i(a,s) = \sum_{t=0}^{\infty} \left[\beta^t \log\left(\mathcal{C}_t^i\right) \right] + \wp_h^i(a,s)$$

$$\begin{aligned} s.t. \quad & \mathcal{C}_t^i + I_t^i(phy) + I_t^i(ict) + b_{t+1}^i - (1+r_t)\, b_t^i = \\ & = w_{h,t}(a,s)\mathcal{B}_{h,t}(a,s)\ell_h^i(a,s) + R_t(phy)\, k_t^i(phy) + R_t(ict)\, k_t^i(ict) + \mathcal{D}_t^i \end{aligned}$$

$$with \quad k_{t+1}^i(phy) = \frac{I_t^i(phy)}{\zeta_t^i} + \left(1-\delta_{phy}\right) k_t^i(phy)$$

$$and \quad k_{t+1}^i(ict) = \frac{I_t^i(ict)}{\zeta_t^i} + (1-\delta_{ict})\, k_t^i(ict)$$

where the investment schedule comprises both assets, b_t^i (which are in zero net supply, thus exchanged only across households), and physical and ICT capital holdings, $k_t^i(j)$, with $j = \{phy, ict\}$. Household-specific productivity when working as type-a for firm-h in industry-s is denoted with $\wp_h^i(a,s)$. Each household inelastically supplies one unit of work, so that $\ell_h^i(a,s) = 1$. The firm benefit of household-a is defined to be $\mathcal{B}_{h,t}(a,s) = \left[g_{h,t}(a,s)\right]^{-\varsigma}$, where $g_{h,t}(a,s)$ reflects the relative share (i.e., the task ratio) of a given task, which is negatively scaled by the elasticity parameter ς, while $\mathcal{D}_t^i$ is the share of firms' profits that goes to household i. Capital stock of household i depreciates at a rate $\delta_{(j)}$ and accumulates over time by a law of motion which is function of $\zeta_{i,t}$, namely the quantity of ICT capital relative to that of non-ICT capital, that enters negatively in new capital investment, $I_t^i(j)$, under the idea that as the stock of capital owned by household i becomes more sophisticated (larger ICT relative to non-ICT capital when ζ_t^i increases), it is required an higher rate of capital investment to keep constant the future stock of given capital type. Modelling the dynamics of capital in this way serves only to derive analytical solutions for the equations (12) and (13) estimating the pair (ρ,σ) of Section 3.

Utility maximization implies the Lagrangian function to be

$$\underset{C_t^i,\, b_{t+1}^i,\, \{k_{t+1}^i(j)\}_{\forall j}}{\mathcal{L}} = \sum_t \beta^t \left[log\, C_t^i \right] + \wp^i(a,s) +$$

$$- \sum_t \beta^t \psi^t \Big[C_t^i + I_t^i(phy) + I_t^i(ict) +$$

$$+ \; b_{t+1}^i - (1+r_t)\, b_t^i - w_{h,t}(a,s)\mathcal{B}_{h,t}(a,s) +$$

$$- \; R_t(phy)\, k_t^i(phy) - R_t(ict)\, k_t^i(ict) - \mathcal{D}_t^i \Big]$$

with ψ^t being the penalty multiplier. Optimality conditions are in order

$$\frac{1}{C_t^i} = \beta^t \,(1+r_{t+1})\, \frac{1}{C_{t+1}^i}$$

$$R_t = (1+r_{t+1})\, \zeta_t - (1-\delta)\zeta_{t+1}$$

The first is the usual Euler condition, which displays future path of consumption. The second implies that, aggregating across households, the path on interest rates on capital types, $R_t(phy) = R_t(ict) \equiv R_t$, is linked to the path of aggregate relative quantity of ICT capital, $\zeta_t = \int_i \zeta_t^i \,\mathrm{d}i$, when $\delta_{phy} = \delta_{ict} \equiv \delta$;[I] in other words, given the constancy of both the discount factor and the capital depreciation rate(s), changes across states of the capital rental rate are determined by changes in the relative quantities across capital types. In the spirit of Karabarbounis and Neiman (2014), eq. (5) determines that investing in capital types is profitable as long as the marginal benefit of investment (the capital rental rate) is at least lower than its marginal cost (interest rate, r_t and depreciation rate, δ).

(Labour supply derivation) *The probability of worker-a choosing firm $h = 1$ in industry $s = 1$ can be written as*

$$\Big(\mathcal{P}_1(a,1) \equiv \Big) \Longleftrightarrow \mathcal{P}(a,1) \qquad \textit{for notation purposes, abstract from firm subscript}$$

$$\mathcal{P}(a,1) = Pr\Big[w(a,1)\mathcal{B}(a,1)\wp^i(a,1) > w(a,s)\mathcal{B}(a,s)\wp^i(a,s) \Big],\ \forall s \neq 1$$

$$= Pr\left[\frac{w(a,1)\mathcal{B}(a,1)}{w(a,s)\mathcal{B}(a,s)} \wp^i(a,1) > \wp^i(a,s) \right],\ \forall s \neq 1$$

For $s \in [2,S]$, the partial derivative of $\mathcal{P}(a,1)$ with respect to $\wp^i(a,1)$ is

[I] Alternatively, the common depreciation rate might be a weighted average of all the capital-types' depreciation rates.

$$\left\{\wp^i(a,1),\ \frac{w(a,1)\mathcal{B}(a,1)}{w(a,2)\mathcal{B}(a,2)}\wp^i(a,1),\ \ldots,\ \frac{w(a,1)\mathcal{B}(a,1)}{w(a,S)\mathcal{B}(a,S)}\wp^i(a,1)\right\}$$

so that $\mathcal{P}(a,1)$ can be re-written as

$$\begin{aligned}\mathcal{P}(a,1) &= F_{\wp^i(a,1)}\Big(\wp^i(a,1),\ \alpha_2\wp^i(a,1),\ \ldots,\ \alpha_s\wp^i(a,1)\Big),\ \forall\wp^i(a,s)\\ &= \int F_{\wp^i(a,1)}\Big(\wp^i(a,1),\ \alpha_2\wp^i(a,1),\ \ldots,\ \alpha_s\wp^i(a,1)\Big)\mathrm{d}\wp^i(a,1)\end{aligned}$$

for $\alpha_s = \frac{w(a,1)\mathcal{B}(a,1)}{w(a,s)\mathcal{B}(a,s)}$. Now, recall that the parameter $\wp^i(a,s)$ is drawn from a multivariate Frechét-type cumulative distribution,

$$F_i\Big(\wp^i_{h,\ldots,H}(a,1),\ldots,\wp^i_{h,\ldots,H}(a,s),\ldots,\wp^i_{h,\ldots,H}(a,S)\Big) = exp\left[-\sum_s\left(\int_h \wp^i_h(a,s)\,\mathrm{d}h\right)^{-\theta}\right]$$

which becomes, in this framework (i.e., not considering firm's notation),

$$\begin{aligned}F\Big(\alpha_1\wp^i(a,1),\ldots,\alpha_s\wp^i(a,s),\ldots,\alpha_S\wp^i(a,S)\Big) &= exp\left[-\sum_s\alpha_s^{-\theta}\ \sum_s\wp^i(a,s)^{-\theta}\right]\\ &= exp\left[-\sum_s\Big(\alpha_s\ \wp^i(a,s)\Big)^{-\theta}\right]\end{aligned}$$

Taking its derivative with respect to $\wp^i(a,s)$ turns to write that

$$F_{\wp^i(a,1)}\Big(\wp^i(a,1),\ \alpha_2\wp^i(a,1),\ \ldots,\ \alpha_s\wp^i(a,1)\Big) = -(-\theta)\,\wp^i(a,s)^{-\theta-1}exp\left[\overline{\alpha}\wp^i(a,s)^{-\theta}\right]$$

with $\overline{\alpha} = \sum_s \alpha_s^{-\theta}$. Evaluating the integral in $\mathcal{P}(a,1)$ yields to

$$\mathcal{P}(a,1) = \int\theta\ \underbrace{\wp^i(a,s)^{-\theta-1}}_{A}\ \underbrace{exp\left[\overline{\alpha}\wp^i(a,s)^{-\theta}\right]}_{B}\ \mathrm{d}\wp^i(a,s)$$

By multiplying and dividing by $\overline{\alpha}$ (so that A can be integrated with B), one gets

$$
\begin{aligned}
\mathcal{P}(a,1) &= \frac{\overline{\alpha}}{\overline{\alpha}} \int \theta \wp^i(a,s)^{-\theta-1} exp\left[\overline{\alpha}\wp^i(a,s)^{-\theta}\right] \mathrm{d}\wp^i(a,s) \\
&= \frac{1}{\overline{\alpha}} \int \overline{\alpha}\theta \wp^i(a,s)^{-\theta-1} exp\left[\overline{\alpha}\wp^i(a,s)^{-\theta}\right] \mathrm{d}\wp^i(a,s) \\
&= \frac{1}{\overline{\alpha}} \int \mathrm{d}F\Big(\wp^i(a,1),\ldots,\wp^i(a,s),\ldots,\wp^i(a,S)\Big) \\
&= \frac{1}{\overline{\alpha}} \\
&= \frac{1}{\sum_s \alpha_s^{-\theta}}
\end{aligned}
$$

By recalling that $\alpha_s = \frac{w(a,1)\mathcal{B}(a,1)}{w(a,s)\mathcal{B}(a,s)}$, *it is possible to obtain that,* $\forall s \neq 1$,

$$
\mathcal{P}(a,1) = \frac{\Big(w(a,1)\mathcal{B}(a,1)\Big)^{\theta}}{\Big(\sum_s w(a,s)\mathcal{B}(a,s)\Big)^{\theta}}
$$

where, including firm's subscript-h, it becomes

$$
\mathcal{P}_1(a,1) = \frac{\Big(w_1(a,1)\mathcal{B}_1(a,1)\Big)^{\theta}}{\Big(\sum_{h,s} w_h(a,s)\mathcal{B}_h(a,s)\Big)^{\theta}}
$$

Taking in general notation, $\forall h \in [1,H]$ *and* $\forall s \in [1,S]$, *it can be written as*

$$
\mathcal{P}_h(a,s) = \frac{\Big(w_h(a,s)\mathcal{B}_h(a,s)\Big)^{\theta}}{\Big(\sum_{h,s} w_h(a,s)\mathcal{B}_h(a,s)\Big)^{\theta}} \quad , \quad with \quad \mathcal{B}_h(a,s) = \left[g_h(a,s)\right]^{-\varsigma}
$$

the fraction of type-a households choosing to work in firm-h-industry-s as in eq. (6).
To interpret the role of θ – the shape parameter of the Frechét distribution –, Figure B.1 plots the distribution of productivities under different values of θ, interpreted as being the degree of dispersion of households-specific efficiencies in working in firm-h in industry-s. Basically, the larger is the value of θ the lower is the variability of the productivity distribution (i.e., the lower is the dispersion of households' productivities), thus the higher is the degree of labour market concentration of workers across firms and industries.

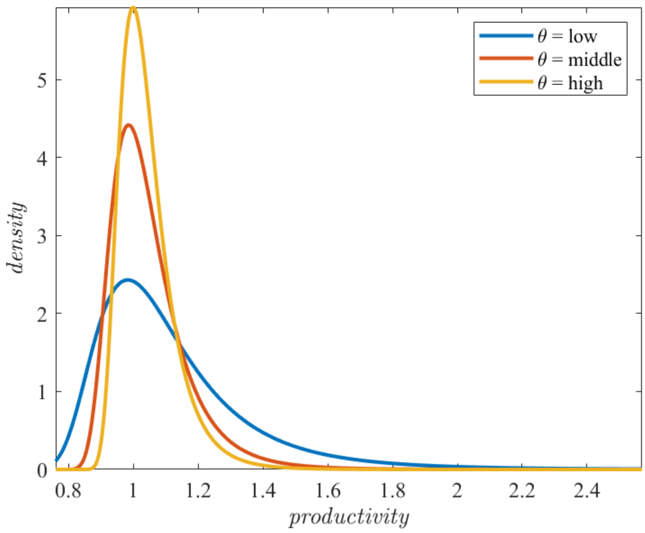


FIGURE B.1: VARIABILITY AND THE SHAPE PARAMETER

Note: this plot represents how the distribution of an arbitrary variable (*e.g.*, productivity) changes along different values of the shape parameter, keeping unchanged the scale parameter; lower shape parameter results in major variability, as in Figure 3.

(Firm optimization) *Given $y_h(s)$ being the production function in eq. (9), and the firm's conditional demand given by eq. (8), the problem of a monopolistically competitive firm (h, s) choosing capital and labour endowments is*

$$\max_{p_h(s),\{k_h(j,s)\}_{\forall j},\{\ell_h(a,s)\}_{\forall a}} p_h(s)y_h(s) - \left(\sum_j R(j)\, k_h(j,s) + \sum_a w_h(a,s)\, \ell_h(a,s)\right)$$

$$s.t. \quad y_h(s) = \left(\frac{p_h(s)}{p(s)}\right)^{\epsilon} y(s)$$

with $a = \{rt, nrt\}$ and $j = \{phy, ict\}$. The inter-temporal Lagrangian function for firm-h industry-s takes the form of

$$\begin{aligned}\mathcal{L}_{p_h(s),\{k_h(j,s),\ell_h(a,s)\}_{\forall j,a}} = p_h(s)y_h(s) - \Big(&R(phy)\, k_h(phy,s) + R(ict)\, k_h(ict,s) + \\ &+ w_h(rt,s)\, \ell_h(rt,s) + w_h(nrt,s)\, \ell_h(nrt,s)\Big) + \\ &- \psi^t \Big[y_h(s)p_h(s)^{\epsilon} - y(s)\Big]\end{aligned}$$

with ψ^t being the penalty multiplier. Optimality conditions are in order

$$\frac{\partial \mathcal{L}}{\partial p_h(s)} \; : \; \psi = \frac{1}{\epsilon} p_h(s)^{1-\epsilon}$$

$$\frac{\partial \mathcal{L}}{\partial k_h(phy,s)} \; : \; p_h(s) f_{k_h(phy,s)} = \mathcal{M} R(phy)$$

$$\frac{\partial \mathcal{L}}{\partial k_h(ict,s)} \; : \; p_h(s) f_{k_h(ict,s)} = \mathcal{M} R(ict)$$

with the price mark-up being

$$\mathcal{M} = \frac{\epsilon}{\epsilon - 1}$$

and first order conditions of firm-industry specific output relative to capital-types are

$$f_{k_h(phy,s)} = \alpha \Big(k_h(phy,s)\Big)^{\alpha-1} \left[y_h(s) \Big(k_h(phy,s)\Big)^{-\alpha} \right]$$

$$f_{k_h(ict,s)} = (1-\alpha)(1-\mu)\lambda \left[\Big(k_h(phy,s)\Big)^{\alpha} \mathcal{V}_h^{\frac{1-\alpha-\varsigma}{\varsigma}} \mathcal{Q}_h^{\frac{\varsigma-\varrho}{\varrho}} \right] \Big(k_h(ict,s)\Big)^{\varrho-1}$$

with

$$\mathcal{V}_h = \mu \Big(\ell_h(rt,s)\Big)^{\varsigma} + (1-\mu)\, \mathcal{Q}_h^{\frac{\varsigma}{\varrho}}$$

and

$$\mathcal{Q}_h = \lambda \Big(k_h(ict,s)\Big)^{\varrho} + (1-\lambda)\Big(\ell_h(nrt,s)\Big)^{\varrho}$$

Note how aggregate capital rental rates, $R_t\,(j)$, are obtained by aggregating marginal product of capital types $\left(f_{k_h(j,s)}\right)$ across firms and industries.

Optimality conditions for wages are found by deriving directly for $\ell_h(a,s)$; this results in computing what follows.

$$\frac{\partial \mathcal{L}}{\partial \ell_h(rt,s)} \; : \; p_h(s) f_{\ell_h(rt,s)} = \mathcal{M}\, w_h(rt,s)$$

$$\frac{\partial \mathcal{L}}{\partial \ell_h(nrt,s)} \; : \; p_h(s) f_{\ell_h(nrt,s)} = \mathcal{M}\, w_h(nrt,s)$$

with the price mark-up still being $\mathcal{M} = \frac{\epsilon}{\epsilon-1}$, and first order conditions of firm (h,s)'s output relative to labour-types are

$$f_{\ell_h(rt,s)} = (1-\alpha)\mu\Big(k_h(phy,s)\Big)^{\alpha}\mathcal{V}_h^{\frac{1-\alpha-\varsigma}{\varsigma}}\Big(\ell_h(rt,s)\Big)^{\varsigma-1}$$

$$f_{\ell_h(nrt,s)} = (1-\alpha)(1-\mu)(1-\lambda)\Big(k_h(phy,s)\Big)^{\alpha}\mathcal{V}_h^{\frac{1-\alpha-\varsigma}{\varsigma}}\mathcal{Q}_h^{\frac{\varsigma-\varrho}{\varrho}}\Big(\ell_h(nrt,s)\Big)^{\varrho-1}$$

with

$$\mathcal{V}_h = \mu\Big(\ell_h(rt,s)\Big)^{\varsigma} + (1-\mu)\,\mathcal{Q}_h^{\frac{\varsigma}{\varrho}}$$

and

$$\mathcal{Q}_h = \lambda\Big(k_h(ict,s)\Big)^{\varrho} + (1-\lambda)\Big(\ell_h(nrt,s)\Big)^{\varrho}$$

Now, note that labour supplies for both types of tasks $a = \{rt, nrt\}$ are all determined by eq. (6), namely $\ell_h(a,s) = f\Big(w_h(a,s),\, \mathcal{B}_h(a,s),\, \mathcal{W}_{\mathcal{H}}(a,\mathcal{S}),\, \mathcal{B}_{\mathcal{H}}(a,\mathcal{S})\Big)$. Therefore, equating demand and supply of labour for each task-a results in deriving the associated optimal wage level in general equilibrium, that is

$$\begin{cases} p_h(s) f_{\ell_h(rt,s)} = \mathcal{M}\, w_h(rt,s) \\ \\ \qquad \ell_h(rt,s) = \left(\dfrac{w_h(rt,s)\mathcal{B}_h(rt,s)}{\sum_{h,s} w_h(rt,s)\mathcal{B}_h(rt,s)}\right)^{\theta} \end{cases}$$

and

$$\begin{cases} p_h(s) f_{\ell_h(nrt,s)} = \mathcal{M}\, w_h(nrt,s) \\ \\ \qquad \ell_h(nrt,s) = \left(\dfrac{w_h(nrt,s)\mathcal{B}_h(nrt,s)}{\sum_{h,s} w_h(nrt,s)\mathcal{B}_h(nrt,s)}\right)^{\theta} \end{cases}$$

By writing down the extensive forms for each derivative of $\ell_h(a,s)$ and exploiting the calculations to solve for $w_h(a,s)$, together with proposition 1, optimal wages are those reported in eq. (10). Note that $\mathcal{V}_h$ expresses the substitutability between routine workers $(\ell_h(rt,s))$ and the ICT composite good $(\mathcal{Q}_h)$, while $\mathcal{Q}_h$ identifies the substitutability between ICT capital $(k_h(ict,s))$ and non-routine workers $(\ell_h(nrt,s))$, considering each firm $h \in \mathcal{H}$ in industry-s.

Finally, firm (h,s) profits can be found by including equilibrium optimality conditions for both capital and wages in

$$\mathcal{D}_h(s) = p_h(s)y_h(s) - \left(\sum_j R(j)k_h(j,s) + \sum_a w_h(a,s)\ell_h(a,s)\right)$$

where $j = \{phy, ict\}$ identifies the types of capital in the economy.

(Proof of Proposition 1) *This heuristic proof is centred around the definition of the workers' measures as given by eq. (6) with no worker-a benefit, $\mathcal{B}_h(a,s) = 1$, $\forall a,h,s$. Imagine an economy in which there is only one industry $s \in \mathcal{S} = 1$ populated by two firms, $\{h,h'\} \in \mathcal{H}$, and define $\mathcal{W}_{\mathcal{H}}(a,s) = w_h(a,s) + w_{h'}(a,s)$. Then:*

(a) when firms are assumed to be homogeneous in their size, i.e., when $\ell_h(a,s) \equiv \ell_{h'}(a,s)$, then they should set the same optimal wage level since

$$\left(\frac{w_h(a,s)}{\mathcal{W}_{\mathcal{H}}(a,s)} =\right) \ \ell_h(a,s) \equiv \ell_{h'}(a,s) \ \left(= \frac{w_{h'}(a,s)}{\mathcal{W}_{\mathcal{H}}(a,s)}\right)$$

holds only if $w_h(a,s) = w_{h'}(a,s)$.

(b) if firms are heterogeneous in size eq. (6) predicts how, in order to have $\ell_h(a,s) \neq \ell_{h'}(a,s)$, it is necessary that wage levels are different, $w_h(a,s) \neq w_{h'}(a,s)$. Assume that firm (h',s) sets a wage rate higher than firm (h,s), so that the former is larger than the latter. Assume further an increase in the wage chosen by firm (h',s), labelling the new level as $w_{h'}(a,s)'$, while the other wage remains unchanged. Henceforth, it must be the case that

$$w_{h'}(a,s) \to w_{h'}(a,s)', \quad \text{so that} \quad \mathcal{W}_{\mathcal{H}}(a,s) < \mathcal{W}_{\mathcal{H}}(a,s)'.$$

For such firm, clearing the condition

$$\mathcal{W}_{\mathcal{H}}(a,s)' = \frac{w_{h'}(a,s)'}{\ell_{h'}(a,s)'} \tag{B.1}$$

means that there should be a related increase in its workforce, $\frac{\partial \ell_{h'}(a,s)}{\partial w_{h'}(a,s)} > 0$, so that $\ell_{h'}(a,s)' > \ell_{h'}(a,s)$. Different scenario happens to the employees level of firm (h,s): it turns out that $\ell_h(a,s)' < \ell_h(a,s)$ when $w_{h'}(a,s) \to w_{h'}(a,s)'$ since $\frac{\partial \ell_h(a,s)}{\partial w_{h'}(a,s)} < 0$. The implied mechanism is just

$$\frac{\partial \ell_{h'}(a,s)}{\partial w_{h'}(a,s)} = -\frac{\partial \ell_h(a,s)}{\partial w_{h'}(a,s)}$$

However, the given change in the wage of firm (h',s) not only has an impact on $\ell_{h'}(a,s)$, but it indirectly translates to the wage level of firm (h,s) due its negative effect on $\ell_h(a,s)$. The firm (h,s) version of the condition in eq. (B.1)

$$\mathcal{W}_{\mathcal{H}}(a,s)' = \frac{w_h(a,s)'}{\ell_h(a,s)'} \tag{B.2}$$

implies that, after an increase in $\mathcal{W}_{\mathcal{H}}(a,s)$ and a decrease in $\ell_h(a,s)$ due to a positive change in $w_{h'}(a,s)$, then the wage level of firm (h,s) must increase as well. It turns out that an increase in the wage level of firm (h',s) must determine an equal increase in the right-hand-side of both eqs. (B.1)-(B.2), which means

$$\frac{w_h(a,s)'}{\ell_h(a,s)'} = \frac{w_{h'}(a,s)'}{\ell_{h'}(a,s)'}$$

so that $\frac{\partial w_h(a,s)}{\partial \ell_h(a,s)} = \frac{\partial w_{h'}(a,s)}{\partial \ell_{h'}(a,s)}$.

To sum up, when firms in a specific industry are of different size in terms of employed workers of type-a, an increase in the wage level of a given firm causes: (i) an increase in the number of employed people in that firm, $\frac{\partial \ell_{h'}(a,s)}{\partial w_{h'}(a,s)} > 0$; (ii) a related decrease in the number of workers of the other firms, $\frac{\partial \ell_h(a,s)}{\partial w_{h'}(a,s)} < 0$, and thus an increase in other firms' wage levels, $\frac{\partial w_h(a,s)}{\partial w_{h'}(a,s)} > 0$. This is true as long as workers of each type-a are free to move across firms in the same industry at no cost and firms can hire new workers from the other firms;

(c) *by applying the same reasoning of point (b), if workers were perfectly mobile across industries, then it would have been the case that $\frac{w(a,s')}{\ell(a,s')} = \frac{w(a,s)}{\ell(a,s)}$. This chance is ruled out by assuming a very high cost of transition from one industry to another such that no one among workers is keen to move.*

(Equilibrium characterization) *In equilibrium, the model should specify the clearing conditions of labour, capital, and goods markets. Starting from the labour market, since each household inelastically supplies one unit of labour, then it must hold that the total number of workers of type-a in firm (h,s) is $\ell_h(a,s) = \int_0^1 \ell_h^i(a,s)\mathrm{d}i$, so that the total labour supply is $L^S = \sum_a \sum_h \sum_s \ell_h(a,s)$. The measure of type-$a$ worker if firm (h,s) is given by eq. (6), while that at industry layer is according to eq. (7). Aggregating it across tasks and firms results in obtaining the industry-specific labour supply, $L(s) = \sum_{a,h} \ell_h(a,s)$. Analogously, aggregate labour supply of task-a is found by aggregating across firms and industries, $L(a) = \sum_{h,s} \ell_h(a,s)$. It follows that, considering $a = \{rt, nrt\}$, aggregate labour demand for this economy is just $L^D = \sum_a L(a) = L(rt) + L(nrt)$. Labour market clearing requires that $L^D = L^S$.*

For what concerns equilibrium in the capital market(s), total physical and ICT capital demands from industries are, respectively, $K^D(phy,s) = \sum_h k_h(phy,s)$ and $K^D(ict,s) = \sum_h k_h(ict,s)$, so that aggregate demands are simply determined: $K^D(phy) = \sum_s K^D(phy,s)$ and $K^D(ict) = \sum_s K^D(ict,s)$. By the part of supply, aggregating capital quantities over households would results in aggregate physical and ICT capital supplies: $K^S(phy) = \int_i k^i(phy)\mathrm{d}i$ and $K^S(ict) = \int_i k^i(ict)\mathrm{d}i$. Equilibrium in both markets *requires* $K(phy) \equiv K^D(phy) = K^S(phy)$ *and* $K(ict) \equiv K^D(ict) = K^S(ict)$*, while market clearing in the capital market implies* $K^D(phy) + K^D(ict) = K^S(phy) + K^S(ict)$.

Finally, aggregate profits to be given to households are $\mathcal{D}^D = \int_i \mathcal{D}_i \,\mathrm{d}i$*, while* $\mathcal{D}^S = \sum_s \mathcal{D}(s)$ *are the total profits computed by aggregating industry-specific profits,* $\mathcal{D}(s) = \sum_h \mathcal{D}_h(s)$. *Equilibrium requires* $\mathcal{D} \equiv \mathcal{D}^D = \mathcal{D}^S$. *This implies that, by aggregating the households' inter-temporal budget constraints and imposing the clearing conditions so far, including also total quantities for*

$$
\begin{aligned}
\mathcal{C}^i &= \int_i \mathcal{C}^i \,\mathrm{d}i \\
I(j) &= \int_i I^i(j) \,\mathrm{d}i\,, \quad \forall j \\
b &= \int_i b^i \,\mathrm{d}i \\
w &= \sum_a \sum_h \sum_s w_h(a,s) \\
\mathcal{B} &= \sum_a \sum_h \sum_s \mathcal{B}_h(a,s)
\end{aligned}
$$

where $\mathcal{B} = 1$ *since it is the sum of relative quantities, the aggregate resource constraint for this economy at time* t *reads as*

$$
\mathcal{C}_t + I_t(phy) + I_t(ict) + b_{t+1} - (1+r_t)b_t = w_t\mathcal{B}_tL_t + R_t\Big(K_t(phy) + K_t(ict)\Big) + \mathcal{D}_t
$$

which equals the total output as defined by the final output CES aggregator, Y. *Equilibrium conditions are described in Section 2.*

C. Model estimation and simulation

(Estimating equations) *To derive the equations to estimate the elasticity of substitution between ICT capital and non-routine workers* (ρ)*, and the elasticity of substitution between routine workers and ICT composite good* (σ)*, i.e., that shown in eqs. (12) and (13), I apply the procedure implemented by Karabarbounis and Neiman (2014). The main steps to be implemented are:*[I]

1. *Define a CES production function,* $y(\cdot)$ *and compute the related F.O.C.s.; then, equate them to the aggregated (across firms and industries) F.O.C.s of the monopolistically competitive firms;*
2. *Define the following income shares. For a given labour force* (ℓ)*, a given capital stock* (k)*, and given profits* ($\mathcal{D}$)*,*

$$s_\ell = \left(\frac{1}{\mathcal{M}}\right)\left(\frac{w(\ell)\ell}{w(\ell)\ell + Rk}\right) \quad , \quad s_k = \left(\frac{1}{\mathcal{M}}\right)\left(\frac{Rk}{w(\ell)\ell + Rk}\right) \quad , \quad s_{\mathcal{D}} = 1 - \frac{1}{\mathcal{M}}$$

3. *By combining the F.O.C. for capital (either for labour) with all the above shares, one gets an equation whose left-hand side is* $1 - s_\ell \mathcal{M}$*. Then, this should be written in changes between two arbitrary periods, whose resulting elements are labelled as* $\widehat{x}$*;*
4. *Use eq. (5) to substitute* $\widehat{R}$*;*
   - $\rightarrow$ *use the Euler condition (from the households side) expressed in deviation between two arbitrary periods get* $\widehat{(1+r)} = \frac{1}{\beta}$ *so that, under constant* β *and* δ*, it holds that* $\widehat{R} = \widehat{\zeta}$*;*
5. *Once substituting out* $\widehat{R}$*, take a linear approximation of the resulting equation around* $\widehat{\zeta} = 0$*, thus obtaining the estimating equation.*

Apply this procedure for whatever CES functional form of the production function $y(\cdot)$*. Note that, to carry out this procedure in the framework I propose it is necessary to assume equal marginal product of each type of capital. In fact, in eq. (5), trends in both capital rental rates are tied with trends in the quantity of ICT capital relative to non-ICT one, after aggregating optimal conditions in the firm problem. Here, the two capital rates are given by capitals' marginal productivity: thus, to have a unique capital rental rate, such that* $R(phy) = R(ict) \equiv R$*, equal marginal product of capital types are in order.*

(Targeting moments for MSM) *Start from the weighting parameters,* λ *and* μ*. For each industry* $s \in \mathcal{S}$*, the weight of ICT capital* (λ) *in the ICT composite is matched with the industry-specific ICT capital in the aggregate stock in the data.*

[I] Please refer to Karabarbounis and Neiman (2014) for further details and discussion.

Differently, the weight of routine workers (μ) in the production function is used to bridge the share of routine workers in the data with that predicted by the model, i.e., I implement the following identity using eq. (6): $\ell_{model}(a,s) = \left(\frac{w(a,s)}{\mathcal{W}(a,\mathcal{S})}\frac{\mathcal{B}(a,s)}{\mathcal{B}(a,\mathcal{S})}\right)^{\theta} \approx \ell_{data}(a,s)$. Of course, since the model's measures of employment are determined by relative wages, some slight differences in the estimated matched moments are in order.

Finally, I consider productivity dispersion parameter, θ, which directly relates to the between-industry wage difference for worker-a. Given $a = rt$, I use the wage premium of type-a working in top industry (s) relative to its counterpart in the bottom industry (s'):

$$\frac{w(rt,s)}{w(rt,s')} = \frac{\left[\Lambda(s)\,\chi(rt,s)\,\left(k(phy,s)\right)^{\alpha(s)}\,\mathcal{V}(s)^{\frac{1-\alpha(s)-\varsigma(s)}{\varsigma(s)}}\,\mathcal{B}(rt,s)^{\theta(\varsigma(s)-1)}\,\mathcal{WB}(rt,\mathcal{S})^{\theta(1-\varsigma(s))}\right]^{\frac{1}{1+\theta-\theta\varsigma(s)}}}{\left[\Lambda(s')\,\chi(rt,s')\,\left(k(phy,s')\right)^{\alpha(s')}\,\mathcal{V}(s')^{\frac{1-\alpha(s')-\varsigma(s')}{\varsigma(s')}}\,\mathcal{B}(rt,s')^{\theta(\varsigma(s')-1)}\,\mathcal{WB}(rt,\mathcal{S})^{\theta(1-\varsigma(s'))}\right]^{\frac{1}{1+\theta-\theta\varsigma(s')}}}$$

If considering changes over time, only $k(phy,\cdot)$, $\mathcal{V}(\cdot)$, $\mathcal{B}(\cdot)$, and $\mathcal{WB}(\cdot)$ are time-varying, with all the other parameters previously calibrated, targeted and fixed: this leaves θ as the only free parameter to match this moment. Note how I choose to pin down labour market concentration for routine workers in accordance with Figure 5.

TABLE C.1: EMPLOYMENT MEASURES AND TASKS RELATIVE WAGES

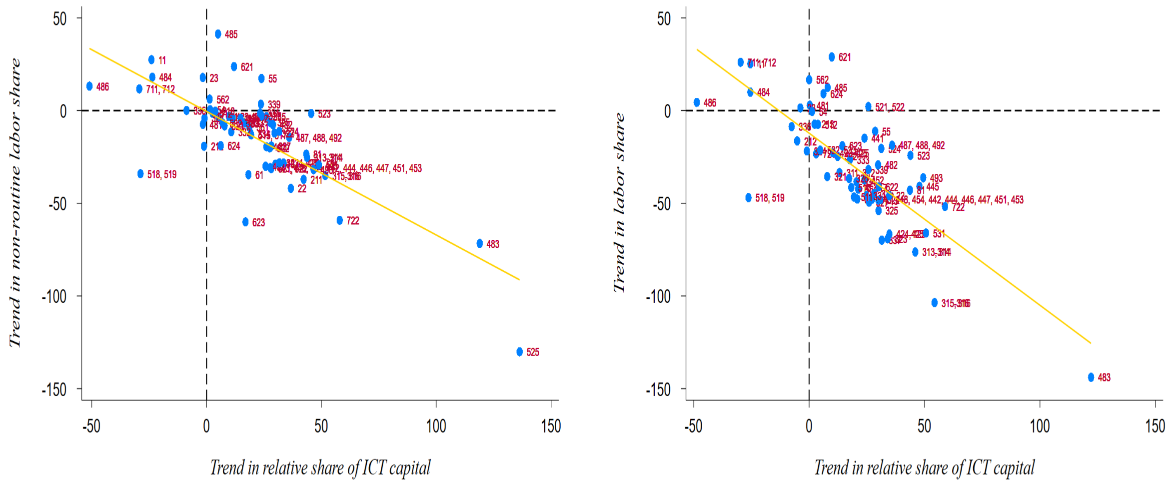
	$log(\ell(rt,s))$			$log(\ell(nrt,s))$		
	(1)	(2)	(3)	(1)	(2)	(3)
$\ell(rt,s\,\vert\,w\mathcal{B})$	.765*	.657*	3.55***			
	(.32)	(.28)	(.17)			
$\ell(nrt,s\,\vert\,w\mathcal{B})$				5.76***	3.71***	29.4***
				(1.9)	(1.1)	(2.2)
Industry FE	✓	✓	✗	✓	✓	✗
Time FE	✗	✓	✗	✗	✓	✗

*Significance level at * (p<0.05), ** (p<0.01), *** (p<0.001). Standard error in parentheses. Analysis at 3-digit US 2017 NAICS industries in 2003-2022 on* $N = 1240$ *observations. All the regressions are of the form* $(y_t \mid \mathcal{X}_{i,t}, \mathcal{Z}_{j,t}) = \beta_c + \beta_i \mathcal{X}_{i,t} + \delta_j \mathcal{Z}_{j,t} + u_t$, *with* $\mathcal{X}_i$ *being the regressors, and* $\mathcal{Z}_j$ *a set of controls. All series are in logs. Constant not reported to save space. Source: BLS and own calculations.*

Table C.2: Method of Simulated Moments, results

	parameter	*value*	***moment to match***	***fit***	
				data	*model*
μ_{bot}	weight of routines in $y(bot)$	0.6763	routine share, bottom	.0858	.0434
μ_{mid}	weight of routines in $y(mid)$	0.4953	routine share, middle	.1357	.0458
μ_{top}	weight of routines in $y(top)$	0.3366	routine share, top	.0985	.0199
λ_{bot}	weight of ICT in $\mathcal{Q}(bot)$	0.4565	ICT share, bottom	.3968	.3968
λ_{mid}	weight of ICT in $\mathcal{Q}(mid)$	0.4645	ICT share, middle	.3042	.3042
λ_{top}	weight of ICT in $\mathcal{Q}(top)$	0.4514	ICT share, top	.2990	.2990
θ	productivity dispersion	11.302	wage premium, $w\,(a,[s,s'])$	.9945	.9945

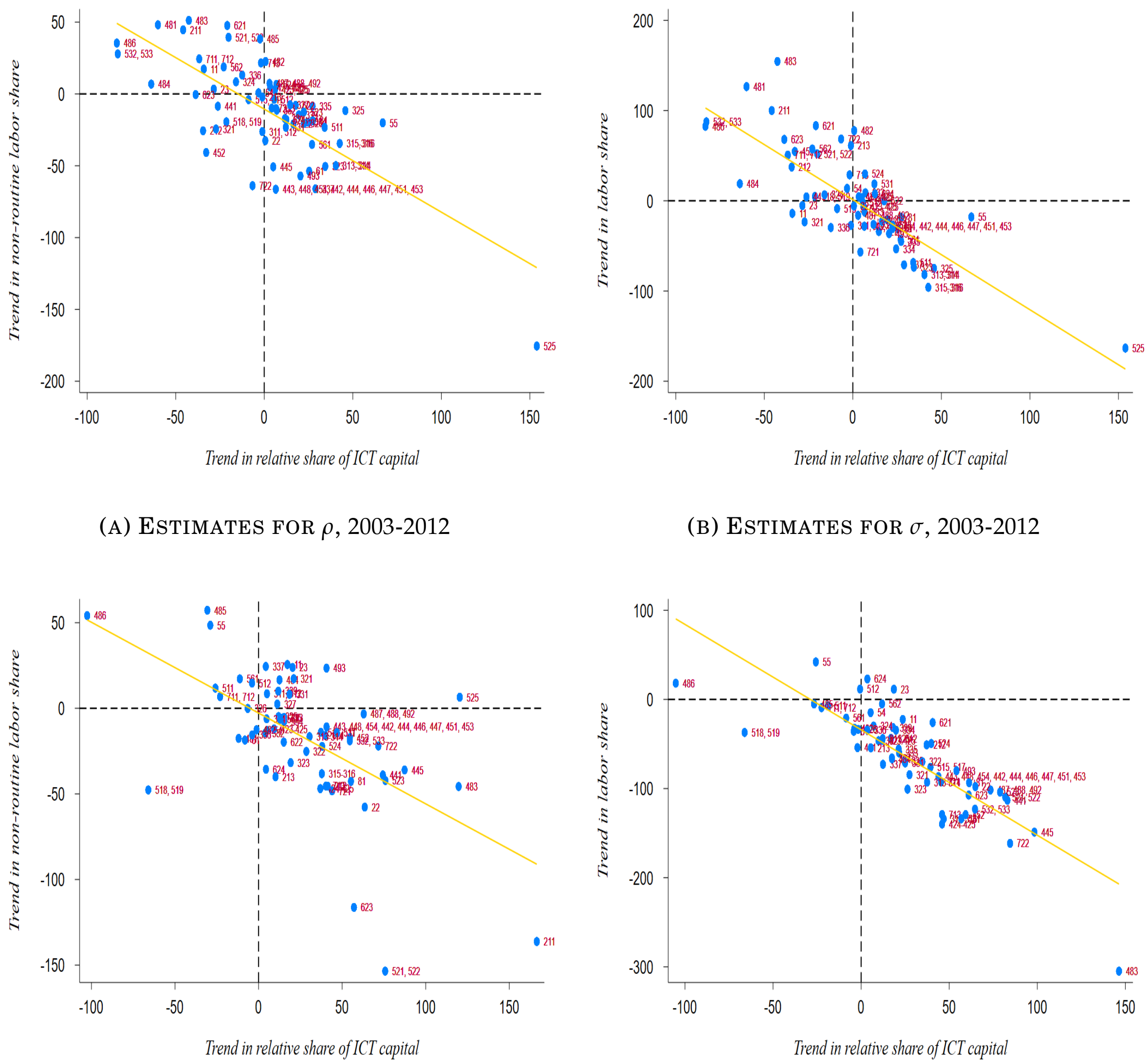
Estimated values and related matched moment using the Methods of Simulated Moments by Mc Fadden (1989).



(A) Estimates for ρ (B) Estimates for σ

Figure C.1: Correlation between elasticities and relative ICT

Note: these scatterplots compute the correlation of trends in labour share with trends in the stock of ICT capital relative to physical capital, namely the left- and right-hand sides estimated through the elasticities of substitution as in eqs. (12) and (13), respectively. Each y-axis report the labour share, while common x-axis is referred to ICT capital. Panel (a) refers the correlation of the elasticity of substitution between ICT capital and non routine workers, while Panel (b) plots that of the entire labour share (considering both routine and non routine workers). Solid-gold negatively-sloped line is the estimated linear trend from robust regression. Labels to each point refer to the 3-digit US 2017 NAICS code of the related industry.



(A) Estimates for ρ, 2003-2012 (B) Estimates for σ, 2003-2012

(C) Estimates for ρ, 2013-2022 (D) Estimates for σ, 2013-2022

Figure C.2: Correlation between elasticities and relative ICT

Note: these scatterplots compute the correlation of trends in labour share with trends in the stock of ICT capital relative to physical capital, namely the left- and right-hand sides estimated through the elasticities of substitution as in eqs. (12) and (13), respectively; first row displays correlation in the period 2003-2012, while the second row that in the period 2013-2022. Each y-axis report the labour share, while common x-axis is referred to ICT capital. Panels (a) and (c) refer the correlation of the elasticity of substitution between ICT capital and non routine workers, while Panels (b) and (d) plot that of the entire labour share (considering both routine and non routine workers). Solid-gold negatively-sloped line is the estimated linear trend from robust regression. Labels to each point refer to the 3-digit US 2017 NAICS code of the related industry.

TABLE C.3: MODEL FIT, UNTARGETED MOMENTS

	fit	
moment	*data*	*model*
aggregate task-premium	.001	.005
aggregate wage	-.008	-.073
routine wage, bottom	-.016	-.070
routine wage, middle	-.001	-.051
routine wage, top	-.007	-.079
non-routine wage, bottom	-.019	-.060
non-routine wage, middle	.003	-.074
non-routine wage, top	-.010	-.046

Untargeted moments to match to validate the calibration strategy. All moments, referred to real log*-wages, are taken as percentage changes throughout the series.*

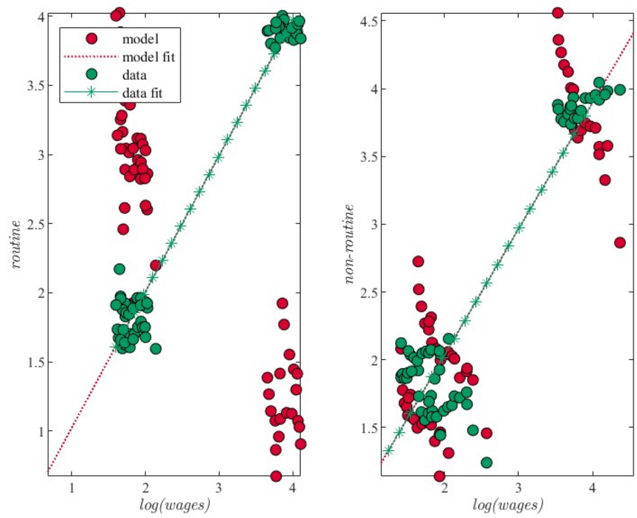
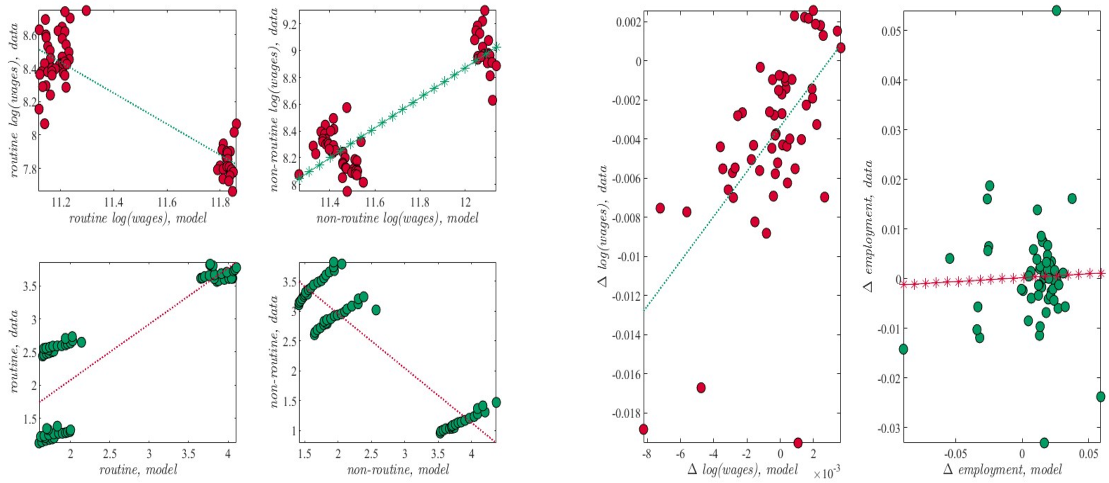


FIGURE C.3: MODEL AND DATA COMPARISON (1/3)

Note: this figure represents the correlation in the baseline equilibrium between the routine and non-routine tasks measures (as in the data and according to eq. (6)) with the empirical and model-implied real log-wage level considering bottom, middle, and top industries' groups. Aqua green circles referred to the model, while orange ones to the data; corresponding lines are shows the linear fit of the correlation.

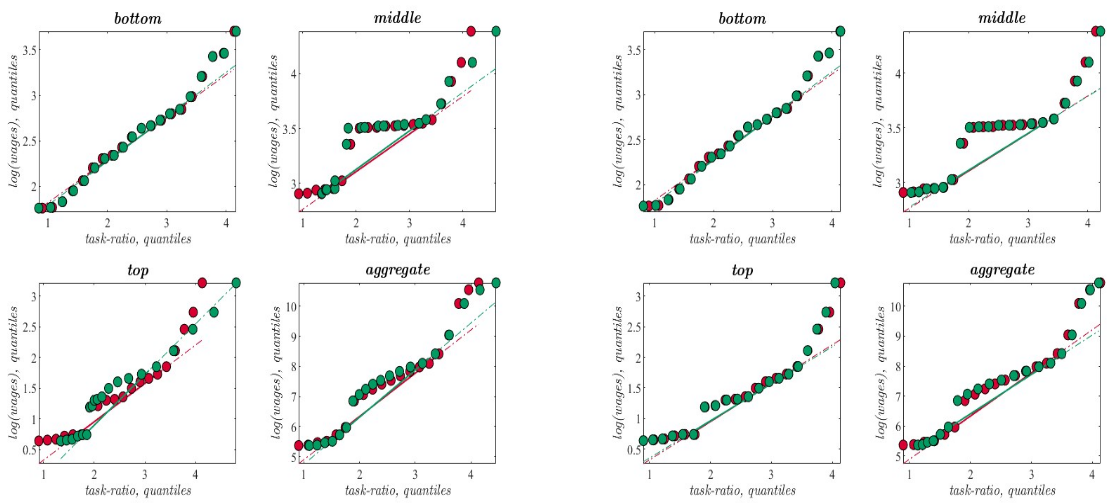


(A) VARIOUS SERIES

(B) CHANGES

FIGURE C.4: MODEL AND DATA COMPARISON (2/3)

Note: these figures compare the dynamics of the real *log*-wage series in the model (solid-red) and in the data (dashed-green). Over the sample period, Panel (a) shows the dynamics of routine worker per capita wages, while Panel (b) plots that of non-routine workers, in each subgroup of industries. Series are scaled to be in the same range for graphical comparison.



(A) ROUTINES, QUANTILES

(B) NON-ROUTINES, QUANTILES

FIGURE C.5: MODEL AND DATA COMPARISON (3/3)

Note: this figure shows the parametric curves associated to quantiles of the considered series (model vs. data) one against each other; here, HP-filtered series are scaled to be in the same range for graphical comparison. Panel (a) represents the quantiles of real *log*-wages associated to routine workers and that of the task ratio; Panel (b) plots the same but for non-routine workers. All plots consider industries to be grouped in terms of bottom, middle, and top industries' groups. Red circles refer to the model, while red ones to the data.

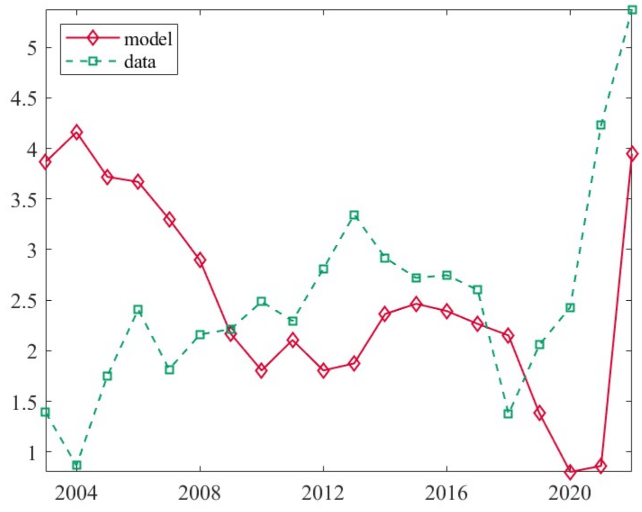
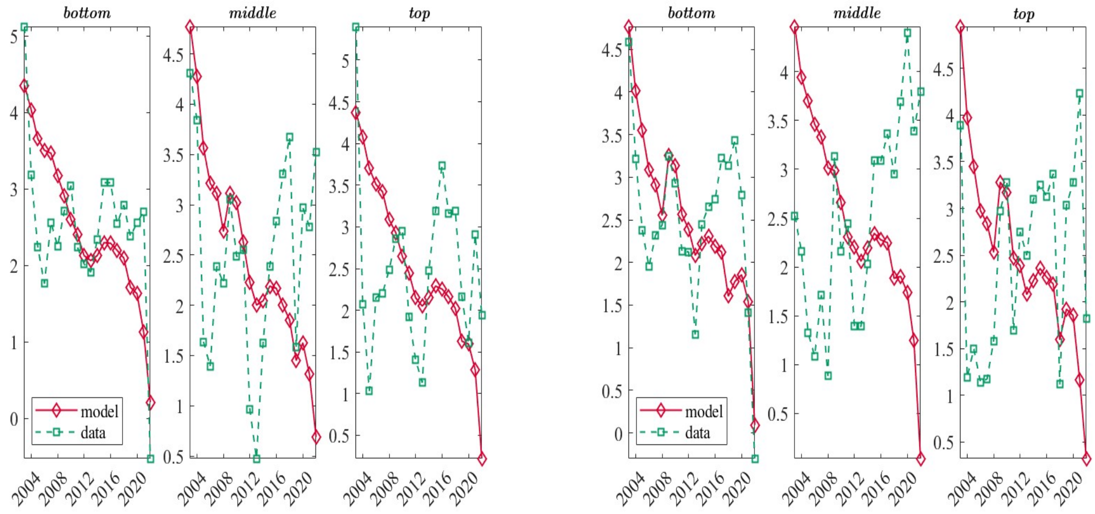


FIGURE C.6: TOP-BOTTOM REAL *log*-WAGE RATIO, MODEL VS. DATA

Note: this figure plots the evolution of the top-bottom industries ratio of real *log*-wages as measured in the model (solid-red) and in the data (dashed-green) in nominal terms. Series are scaled to be in the same range for graphical comparison.

FIGURE C.7: REAL *log*-WAGE SERIES, MODEL VS. DATA (1/3)

Note: this figure compares the dynamics of the real aggregate *log*-wage series in the model (solid-red) and in the data (dashed-green). Series are scaled to be in the same range for graphical comparison.

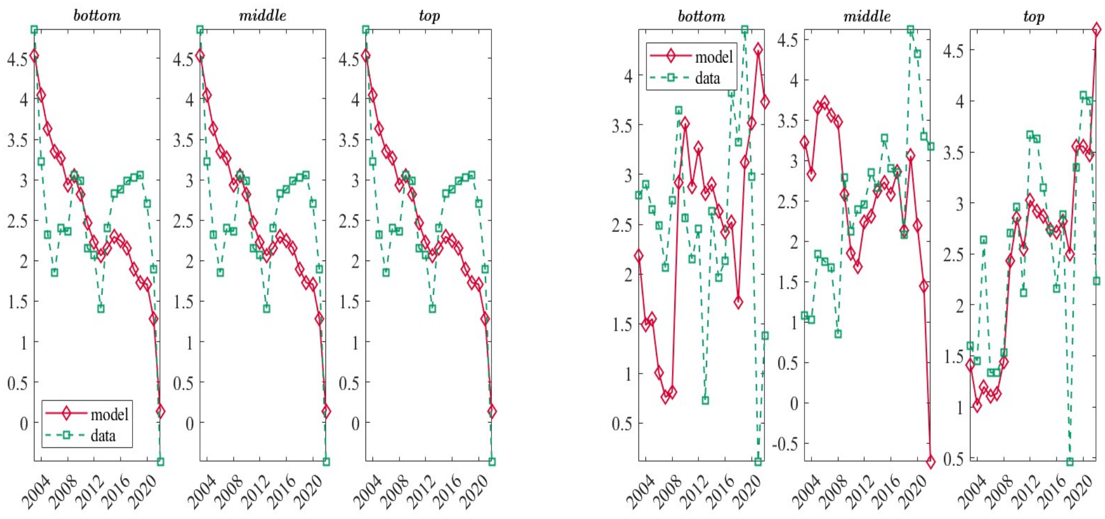


(A) WAGES, ROUTINES

(B) WAGES, NON-ROUTINES

FIGURE C.8: REAL *log*-WAGE SERIES, MODEL VS. DATA (2/3)

Note: these figures compare the fitting between various series as in the model and in the data. Panel (a) shows the correlation between real *log*-wages of routine and non-routine workers, and the associated employment measures, while Panel (b) plots that of aggregate industry wages and employment. The latter measures in the model are given by eq. (6).



(A) WAGES, INDUSTRY GROUPS

(B) TASK PREMIUM

FIGURE C.9: REAL *log*-WAGE SERIES, MODEL VS. DATA (3/3)

Note: these figures compare the dynamics of the real *log*-wage series in the model (solid-red) and in the data (dashed-green). Over the sample period, Panel (a) plots the evolution in the industry real per capita *log*-wage, while Panel (b) depicts the evolution of the task premium, referred to as the wage premium of non-routine over routine tasks, in each subgroup of industries. Series are scaled to be in the same range for graphical comparison.

(Market concentration) *To evaluate the pattern in concentration at industry level, the standard measure Herfindahl-Hirschman Index (HHI) is computed to account for market concentration of labour force for industries. To compute the dynamics in each year, labour market-level concentration for task-a is defined as*

$$HHI_{\ell(a)} = \sum_{s_{|g}} \left(\frac{\ell(a, s_{|g})}{\ell(a)} \right)^2 \tag{C.1}$$

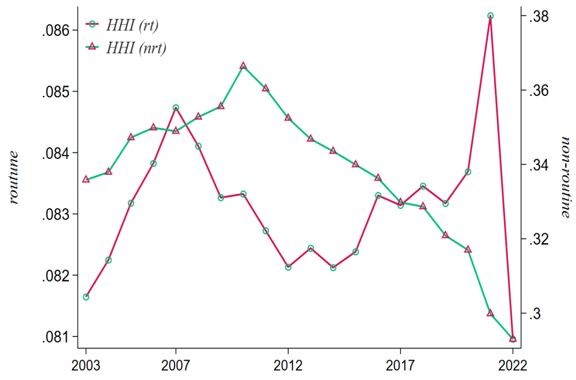
where the sum is over individual industries (s)*, or over a group of industries* $\left(s_{|g}\right)$*. Analogously, total employment concentration is defined by* $HHI_{\ell} = \sum_a HHI_{\ell(a)}$*. This measure is included in the range* $[0, 1]$*: a value of 1 identifies maximum market concentration, namely a single monopsonist in the labour market; conversely, a value of 0 results in a perfectly competitive environment. By definition, if industries have equal labour force size, the index would converge to the number of industries. An index below 0.15 points for an un-concentrated labour market, an index between 0.15 and 0.25 indicates a moderate concentration, while a value higher than 0.25 results in an highly concentrated labour market.*

Each subplot of Figure C.10 depicts the evolution in HHI score for both routine and non-routine workers. As a general observation, labour market concentration for both tasks has increased for top and bottom groups, but it has decreased for middle. With respect to bottom group, Panel C.10a indicates a joint increase in market concentration for both job tasks, with a very high concentration for non-routine workers $\left(HHI_{\ell(nrt)} > 0.25\right)$*; routine workers are approaching to a moderate concentration.*

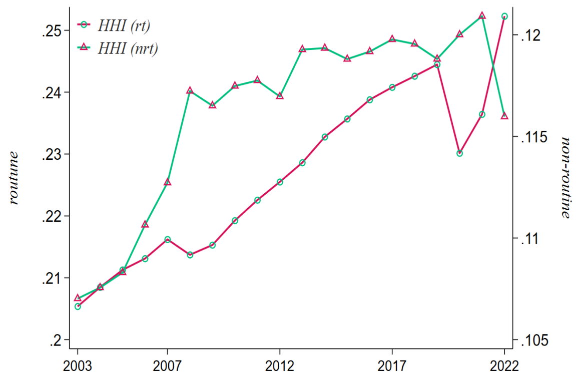
In relation to middle group, after a steady increase, labour market concentration for non-routine workers constantly drops, even if concentration is still high since $HHI_{\ell(nrt)} > 0.25$*. The score for routine workers is low, but if follows cyclical fluctuations, with a steady increase before a recession, and thereafter a substantial drop. If connected with the results of Section E, the pattern of labour market concentration of middle industries may explain the low contribution to trends in US wage inequality.*

Finally, top group has seen a marked and steady increased in market concentration for non-routine workers, which is approaching to a moderate concentration; for the part of routine workers, concentration is high and, after a steady rise in the early years, then a flat pattern has occurred.

(A) BOTTOM



(B) MIDDLE



(C) TOP

FIGURE C.10: MARKET CONCENTRATION BY GROUPS OF INDUSTRIES

Note: this figure represents the evolution in labour market concentration as measured by the Herfindahl-Hirschman Index (HHI). Each subplot measures the dynamics in each broadly defined group of industries by routine (red line, left axis) and non-routine (green line, right axis) tasks. *Source*: BLS and own calculations.

Table C.4: Summary of calibration, 2003-2012

	parameter	***value***				***source***
		bottom	*middle*	*top*	*global*	
α	*physical capital, share of* $y(s)$	0.131	0.091	0.254		*data*
ϵ	*demand elasticity across firms*				6	*external*
μ	*weight of routine workers in* $y(s)$	0.196	0.486	0.902		*MSM*
λ	*ICT capital share in* $Q(s)$	0.650	0.530	0.185		*MSM*
θ	*households' productivities dispersion*				7.26	*MSM*
ρ	*EoS, ICT capital and non-routine*	0.355	0.431	0.408		*estimation*
σ	*EoS, routine and ICT composite*	0.366	0.429	0.367		*estimation*

Set of estimated parameters of the model, first-half of the sample. "data" implies that the values are directly computed from data sources, while in "external" I choose standard calibrated values from the literature. "MSM" refers to the Methods of Simulated Moments as in Mc Fadden (1989). "estimation" refers to previously estimated values under a specific procedure; these values are taken from Table 7.

Table C.5: Summary of calibration, 2013-2022

	parameter	***value***				***source***
		bottom	*middle*	*top*	*global*	
α	*physical capital, share of* $y(s)$	0.131	0.104	0.260		*data*
ϵ	*demand elasticity across firms*				6	*external*
μ	*weight of routine workers in* $y(s)$	0.415	0.506	0.608		*MSM*
λ	*ICT capital share in* $Q(s)$	0.786	0.490	0.327		*MSM*
θ	*households' productivities dispersion*				7.79	*MSM*
ρ	*EoS, ICT capital and non-routine*	0.819	0.345	0.508		*estimation*
σ	*EoS, routine and ICT composite*	0.326	0.438	0.357		*estimation*

Set of estimated parameters of the model, second-half of the sample. "data" implies that the values are directly computed from data sources, while in "external" I choose standard calibrated values from the literature. "MSM" refers to the Methods of Simulated Moments as in Mc Fadden (1989). "estimation" refers to previously estimated values under a specific procedure; these values are taken from Table 7.

TABLE C.6: METHOD OF SIMULATED MOMENTS, SPLITTING RESULTS

		2003-2012			2013-2022		
	moment to match	*value*	*data*	*model*	*value*	*data*	*model*
μ_{bot}	routine share, bottom	0.196	0.087	0.097	0.415	0.085	0.051
μ_{mid}	routine share, middle	0.486	0.132	0.057	0.506	0.140	0.030
μ_{top}	routine share, top	0.902	0.100	0.013	0.608	0.097	0.083
λ_{bot}	ICT share, bottom	0.650	0.399	0.399	0.786	0.395	0.395
λ_{mid}	ICT share, middle	0.530	0.314	0.314	0.490	0.295	0.295
λ_{top}	ICT share, top	0.185	0.287	0.287	0.327	0.311	0.311
θ	wage premium, $w\,(a,[s,s'])$	7.259	0.994	0.994	7.787	0.995	0.995

Estimated values and related matched moment using the Methods of Simulated Moments by Mc Fadden (1989) for first and second half of the sample.

(Exogenous variations) *Starting from the baseline equilibrium in 2003, I am going to exogenously impose that some key parameters, namely $(\rho_s, \sigma_s, \theta)_{\forall s \in \{bot,mid,top\}}$, are changing over time and homogeneously for all industries, so as to evaluate their own contribution to changes in specific moments (levels and variances).*

Key understanding behind the comparison of the results between this exercise and that in the main text is to unearth the role of industry-specific patterns of structural change: the outcome of the data-driven counterfactual analysis comes up in contrast with the result of the present exercise – where I consider homogeneous increases in both elasticities of substitution. Namely, absent any form of heterogeneity across industries in the pattern of both elasticities, the substitution between routine and non-routine workers plays a major role in determining wage dispersion, with a secondary role for the elasticity between ICT capital and non-routine workers (first exercise, Table C.8). Opposite conclusions arises when considering industry-heterogeneous patterns in both elasticities (second exercise, Table 8): firstly, changes in both ρ and σ explain a marked fraction of real $\log$-wage variance but, secondly, it is the joint change in the two elasticities that explains major shares of wage inequality for the US economy. This is a claim to account for both industry-specific cross-sectional and trend levels for the substitutability of factors of production.

(Exogenous variations, levels) *Starting from the effect of changing parameters on wage levels, changes due to an increase in the elasticities of substitution have negative effect on the levels of real $\log$-wages for both routine and non-routine jobs, a direct consequence of $(\sigma, \rho) < 1$, which implies that an increased substitutability makes ICT capital, routine and non-routine workers less complement, thus driving down wages. This negative effect is further explained by looking at the combination of the two increases (column 5): major negative effect is on routine workers, since most of the occurred variation is due to changes in the elasticity of substitution between*

TABLE C.7: MODEL VS. DATA COUNTERFACTUAL, LEVELS

	data	***model***	***model*** $\mid \Delta\, x(j)_{\in\Theta}$				
			$\Delta\sigma$	$\Delta\rho$	$\Delta\,(\sigma,\rho)$	$\Delta\theta$	$\Delta\,(all)$
WAGES, LEVEL ($\Delta_{\%}$)							
routine	-.008	-.067	-.031	-.033	-.031	-.033	-.032
non-routine	-.007	-.061	-.030	-.029	-.029	-.031	-.030
industry	-.007	-.067	-.031	-.032	-.031	-.033	-.031
bottom	-.017	-.065	-.030	-.031	-.030	-.032	-.031
middle	.001	-.070	-.032	-.033	-.031	-.034	-.032
top	-.006	-.065	-.031	-.032	-.031	-.032	-.031
EMPLOYMENT, LEVEL ($\Delta_{\%}$)							
routine	.006	.087	.055	.058	.055	.057	.054
non-routine	.025	.061	.044	.042	.044	.041	.043
industry	.018	.074	.051	.053	.051	.052	.051

Changes in key moments of real log-wages and nominal employment measures in the model induced by an exogenous variation (which is assumed to be homogeneous across groups of industries) in a specific parameter; such shift is computed at the initial period, so that the change identifies the transition from the initial (2003) to the final (2022) steady state level. In the first two columns, the variation is computed throughout the period-by-period percentage differential thus identifying overall changes in empirical trends implied both by the data and the model, while the last three columns are just the percentage difference between the two steady states.

routine workers and ICT capital-non routine task pair. Considering aggregate industry wage in row 3, increasing elasticities alone reduces in the same proportion and, if considered jointly, their shifts account for a major share of the occurred change. Turning to the effect of θ, its change weakens the reduction in wages: less variability in households' productivity dispersion would raise labour market concentration and thus strengthen the sorting and segregation effects, thus positively impacting real log-wage levels, with the result of easing the drop in routine, non-routine and industry wages.[II] *The overall effect of changing these three parameters simultaneously can be summarized as follows. Changes due to homogeneous increases in the elasticities of substitution across factors of production have a negative effect on wages but, considering also the reduced labour market concentration, the negative impact of $\Delta\,(\sigma,\rho)$ is mitigated by stronger complementaries among workers (higher sorting and segregation effects) through increasing θ (i.e., a major labour market concentration), since similar workers would end up in the same workplace.*[III]

In the same fashion are analysed the changes occurred in employment levels. Model-implied measure of each employment category is computed aggregating eq. (6)

[II] The effect of a reduced diffusion in the labour supplied by households can be interpreted in stronger sorting and segregation effects since workers move towards their optimal industries, which may drive up the efficiency in production thus positively impacting the levels of real log-wages.

[III] Stronger coworker complementarities is a fact detected by Freund (2024), whose research has shown that increasing complementarity explains almost 40% of the observed increase in the between-firm share of wage inequality.

under nominal wages. Increasing substitution parameters, both alone and in combination, implies that capital can perform tasks previously performed by workers, thus reducing the employment share of each task-group, and of total employment, explained by the model. In consistency with the assumption of the model, higher substitutability among routine and non-routine workers (σ) *explains more employment of routine labour force, while increased* ρ *implies a reduced complementarity between ICT capital and non-routine tasks, explaining more non-routine labour force. Increased workers' concentration across industries explains a major share of employment types since it would result in an higher fraction of employed people. Finally, accounting for all the increasing variations of structural parameters, employment levels faces a mitigating role of stronger labour market concentration.*

(Exogenous variations, variances) *Consider fixed exogenous variations in the selected set of chosen parameters,* $(\rho_s, \sigma_s, \theta)_{\forall s}$*. In order to do this, I generate an artificial and positive impulse response function (with some persistence) to be multiplied by the estimated value of the parameters as in Table 4, to then compute the new value resulting from their own cumulative sum. Variations are taken alone or in different combinations. The results of this exercise are reported in Table C.8 for different wage variances, and in Table C.7 for both changes in wage levels and employment measures − computed in the model as given by firm-industry-task relative wages (i.e., eq. 6). In both tables, the first two numerical columns compare the moment in both the data and the model. Moments in levels are in terms of total percentage change: besides slightly magnitude differentials, the model's ability in matching the slope of these additional untargeted moments is very good; again, vague exception is for middle group: since it is the most hit by business cycle fluctuations (see Appendix E), the theoretical framework built is not able to match the cycle but only the trend, thus requiring additional assumptions on the stochastic dimension of the model. Unlike, variances are referred to overall implied values: the model well address the real* $\log$*-wage variances for both routine and non-routine workers even in the absence of important aspects detected by the literature not present in the outlined model.*[IV] *Importantly, the overall real* $\log$*-wages between-industry variance in the model is highly close to that in the data, thus allowing to draw conclusions via the structural estimation of the model built that are consistent with observed US wage inequality due to industry factors.*

Industry-homogeneous shifts in (σ, ρ) *accounts for major shares of the increased wage variance. Given the model prediction, increases in* σ *are bear more by routine workers (2.31) variance due to their higher substitutability with non-routine workers; the other way round is for non-routines, mostly impacted (2.18) by the role of* ρ*. The most important result of this counterfactual exercise lies in the last row of the wage variance section, that quantifying the determinants of the overall between-industry*

[IV] Individual characteristics central in the Skill Biased Technological Change (SBTC) literature, such as idiosyncratic education or productivity levels. Alternative explanations, as in Böhm et al. (2022), outline how a prolonged rise in firms' profits, shared with some employees, determine more than a half of the increase in wage premium − even controlling for skills − which is unrelated to worker's idiosyncratic productivity both for Sweden and US, and also at industry level.

TABLE C.8: MODEL VS. DATA COUNTERFACTUAL, PARAMETERS

	data	***model***	***model*** $\mid \Delta\, x(j)_{\in\Theta}$				
			$\Delta\sigma$	$\Delta\rho$	$\Delta\,(\sigma,\rho)$	$\Delta\theta$	$\Delta\,(all)$
WAGES, VARIANCE							
routine	2.285	2.289	2.31	2.16	2.31	2.20	2.36
non-routine	2.314	2.311	2.29	2.18	2.29	2.19	2.32
industry	2.299	2.300	2.30	2.17	2.30	2.20	2.34

Changes in variances in real $\log$-wages in the model induced by an exogenous variation (which is assumed to be homogeneous across groups of industries) in a specific parameter; such shift is computed at the initial period, so that the change identifies the transition from the initial (2003) to the final (2022) steady state level. In the first two columns, the variation is computed throughout the period-by-period percentage differential thus identifying overall changes in empirical trends implied both by the data and the model, while the last five columns are just the percentage difference between the two steady states.

real $\log$-wage dispersion: almost all the variance is majorly explained by changes in the elasticity of substitution between routine and non-routine labour forces (2.30), namely homogeneous increases in σ, while smaller room is devoted to variations in the elasticity of substitution between ICT capital and non-routine workers, namely changes in ρ, since the moment implied by variations in σ only is exactly the same of that with both variations, $\Delta\,(\sigma,\rho)$. In other words, if industries would have experienced a simultaneous increase in their own elasticities of substitution, shifts in overall between-industry wage variance would have been majorly explained by changes in the substitutability between routine and non-routine tasks, and not by that between non-routines and ICT capital. In addition, as with wage levels, an increase in θ would result in less dispersed households' productivities and hence in a tighter concentration of workers across industries, thus determining a reduction in the explained variance (2.20) but, when considering simultaneous increases in all the three parameters, captured by $\Delta\,(\sigma,\rho,\theta)$, a more concentrated labour market generates an higher level (2.34) of real wage variances given homogeneous increases in both σ and ρ across industries. Overall, the analysis of the wage variances has underlined the major role played by σ in explaining trends in wage inequality at industry level. For a given point increase, such elasticity explains almost all of the total level in both the model and the data, while the effect of changing ρ is relatively smaller. Increased concentration inflates the effects of homogeneous structural transformations across industries.

***Sensitivity**. The effect of the substitutability among routine and non-routine workers can be further inspected by a comparable exercise which takes fixed the parameters at the baseline calibration (Table 4) while switching off the occurred variation in capital and labour series at time. In Table C.9 I report the results of such analysis considering changes in routine, non-routine, and ICT capital series both alone and in combination, and conclusions completely ratify those in Table C.8: in order to address the between-industry real $\log$-wage variance, fundamental appears to be the joint evolution in routine and non-routine workers at industry level (2.30),* *while considering the ICT capital series alone (2.78) and in combination with non-routine workers (2.42) brings up the level of inequality.*[V] *Further, it is worth to note that without any change in all the series, the model is still able to address, even if with a slightly higher magnitude (2.79), the between-industry wage variance.*

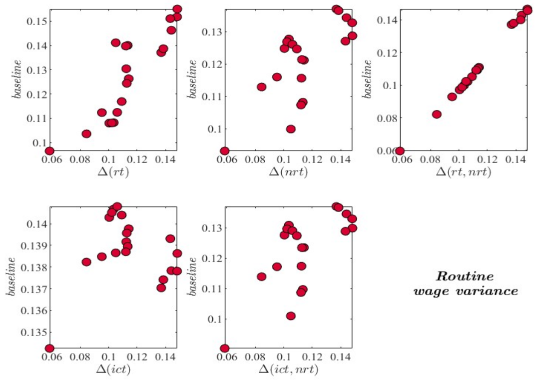
Central interpretations are those related to trends in the industry-level dispersion of wages. Effects on between-industry variance of real $\log$*-wages can be summarized as follows: (i) homogeneous changes in the elasticity of substitution between routine and non-routine workers captures major shares of overall wage variance, and (ii) stronger labour market concentration raises overall wage inequality across industries. All these results and the effects on labour market variables (employment and wages) are referred to an artificial scenario in which all the considered parameters homogeneously and evenly increase for all the groups of industries and by job tasks. In the main exercise (Section 4.2) I am going to employ different parametrizations of the model to disentangle the contribution of each structural parameter considering the actual variation – as it appears in Table 7 and Figure 5 – observed in the data.*

TABLE C.9: MODEL VS. DATA COUNTERFACTUAL, SERIES

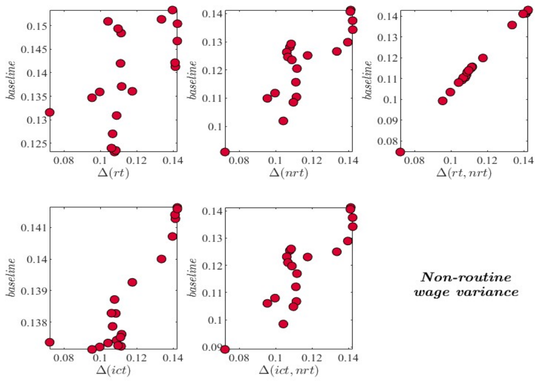
			model $\mid \Delta\,\Phi\,(x)$					
	data	***model***	$\Delta\ell(rt)$	$\Delta\ell(nrt)$	$\Delta\,(\ell)$	$\Delta k(ict)$	$\Delta\,(tech)$	$(all)_{\tau_0}$
WAGES, VARIANCE								
routine	2.285	2.289	2.55	2.42	2.24	2.78	2.45	2.75
non-routine	2.314	2.311	2.78	2.44	2.37	2.78	2.39	2.83
industry	2.299	2.300	2.66	2.43	2.30	2.78	2.42	2.79

Quantification of Model D, but with industry-specific parameters. Changes in variances in real $\log$*-wages in the model induced by variations in one or more series, keeping fixed the others, and imposing the parameters to be that in the baseline calibration.* $\Delta\,(\ell)$ *refers to joint variations in routine and non-routine series, while* $\Delta\,(tech)$ *is associated to simultaneous changes in both ICT capital and non-routine workers.* $(all)_{\tau_0}$ *keeps fixed all the series (physical capital included), at their initial level,* $\tau_0 = 2003$*. In all the columns, the variation is computed throughout the period-by-period percentage differential thus identifying overall changes in empirical trends implied both by the data and the model; same values differ in terms of decimals. The correlations among the baseline wage variance series and that given the variations in each series are depicted in Figure C.11.*

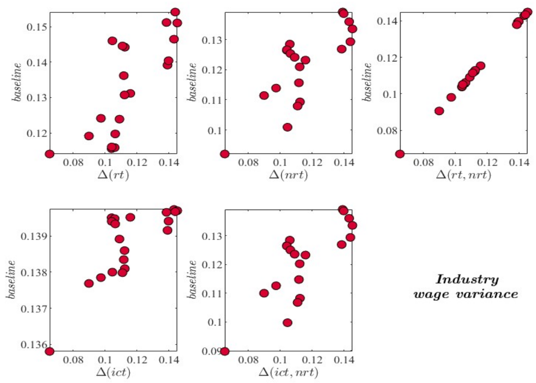
[V] Note that by allowing all the considered series (including physical capital) to change simultaneously would result in the wage variance levels in the baseline scenario (column 3).



(A) ROUTINE



(B) NON-ROUTINE



(C) INDUSTRY

FIGURE C.11: CORRELATION AMONG WAGE VARIANCES, CHANGING SERIES

Note: this figure plots the correlations among the between-industry real *log*-wage variance series in the baseline model and that given the variations in one or more series at time. Parameters are keeping fixed at their baseline values, *i.e.,* those reported in Table 4.

(Further results of Section 4.2) *As in the main text, below I have performed an opposite exercise of Table 8 where the main structural parameters in the model, namely* $(\rho_s, \sigma_s, \theta)_{\forall s \in \{bot,mid,top\}}$ *are keeping fixed one or more at time, and let to change the non-ICT capital share and the weighting parameters in the production function, respectively* $(\alpha_s, \mu_s, \lambda_s)_{\forall s \in \{bot,mid,top\}}$*; the output of such exercise is shown in Table C.10.*

The two analysis performed are conducted by considering industries as a whole, that is, keeping the total employment in terms of both routine and non-routine workers, in order to address the determinants of between-industry wage inequality. However, as noticed, these two exercises can be performed also by distinguish the effects of changing parameters on separate job tasks: Table C.11 reports the two for routine workers, while Table C.12 the same but for non-routine workers.

Below it is possible to find a detailed comment for each employment group and, further below, a comparative comment that shows how the patterns holding for industry with aggregate employment hold also for routine and non-routine workers separately. Visually, these results are in Figures C.12a and C.13a for aggregate industries, and in Figures C.12b and C.13b by job task categories.

TABLE C.10: MODEL COUNTERFACTUAL, FIXING

		Δ ***model*** $\mid \Delta\, m\left(\Phi(x,\tau_2), \Theta = \{p_{\tau_2}, -p_{\tau_1}\}\right)$		
industry wages	$var(w)_{\tau_2}$	*level*	*share, model*	*share, data*
DATA	1.18			
MODEL	1.09			
$\Delta\Theta_{\mid\sigma}$		.94	.86	.79
$\Delta\Theta_{\mid\rho}$		2.21	2.04	1.87
$\Delta\Theta_{\mid(\sigma,\rho)}$		1.31	1.21	1.11
$\Delta\Theta_{\mid\theta}$		1.04	.96	.88
$\Delta\Theta_{\mid(\sigma,\rho,\theta)}$		1.30	1.20	1.10

Quantification of Model B. Model implied between-industry real log*-wage variance changes between two time spans differently calibrated, and changes also according to variations in some parameters; values are referred to variance levels considering bottom, middle, and top industries. Column 2 shows the level in the second period of the between-industry variance both in the data and in the period-two fully calibrated model. For the model specified in column 1: column 3 represents the variance level in the second period as implied by the change in the parameter(s), while column 4 computes the second period variance share of the period-two full model which is accounted by fixing a specified parameter,* $\frac{m\left[\Phi(x,\tau_2) \mid \Theta(p,\tau_2), \Theta(-p^{\{\rho,\sigma,\theta\}},\tau_1)\right]}{m\left[\Phi(x,\tau_2) \mid \Theta(p,\tau_2)\right]}$*, where* $\Phi(x,\tau_2)$ *identifies the series in the second period, and* Θ *the set of parameters where some of them,* (p,τ_2)*, are taken in the second period, while* $(-p,\tau_1)$ *reflects the set of all the parameters in the first period but those considered in the second period. Column 5 reports the fraction of variance explained by changes in parameter(s) in the observed data-driven variance.*

TABLE C.11: MODEL COUNTERFACTUALS FOR ROUTINE WORKERS

routine wages	$var(w)_{\tau_2}$	Δ ***model*** $\mid \Delta\, m\Big(\Phi(x,\tau_2), \Theta = \{p_{\tau_2}, -p_{\tau_1}\}\Big)$ *level*	*share, model*	*share, data*
		CHANGE		
DATA	1.14			
MODEL	.95			
$\Delta\sigma$		.99	1.04	.87
$\Delta\rho$		.35	.37	.30
$\Delta(\sigma,\rho)$		.66	.70	.58
$\Delta\theta$		.57	.60	.50
$\Delta(\sigma,\rho,\theta)$		.71	.76	.63
		FIXING		
DATA	1.14			
MODEL	.95			
$\Delta\Theta_{\mid\sigma}$		.71	.75	.62
$\Delta\Theta_{\mid\rho}$		1.15	1.22	1.01
$\Delta\Theta_{\mid(\sigma,\rho)}$		.84	.89	.74
$\Delta\Theta_{\mid\theta}$		.90	.95	.79
$\Delta\Theta_{\mid(\sigma,\rho,\theta)}$		.81	.86	.71

Quantification of Model A and Model B. Model implied industry-level between-routine workers real log-wage variance changes between two time spans differently calibrated, and changes also according to variations in some parameters; values are referred to variance levels considering bottom, middle, and top industries. Column 2 shows the level in the second period of the between-industry variance both in the data and in the period-two fully calibrated model. For the model specified in column 1: column 3 represents the variance level in the second period as implied by the change in the parameter(s), while column 4 computes the second period variance share of the period-two full model which is accounted by the change in a specified parameter, $\frac{m\left[\Phi(x,\tau_2)\,\middle|\,\Theta(p,\tau_2),\Theta(-p,\tau_1)\right]}{m\left[\Phi(x,\tau_2)\,\middle|\,\Theta(p,\tau_2)\right]}$*, where* $\Phi(x,\tau_2)$ *identifies the series in the second period, and* Θ *the set of parameters where some of them,* (p,τ_2)*, are taken in the second period, while* $(-p,\tau_1)$ *reflects the set of all the parameters in the first period but those considered in the second period. Column 5 reports the fraction of variance explained by changes in parameter(s) in the observed data-driven variance.*

(Comment for routine workers) *Results for routine workers are reported in Table C.11. Second column shows the between-industry real log-wage variance for routine workers only related to second period* (p_2) *both in the data and in the model specified in column 1. Changing one or more parameters at a time, to evaluate the role of each structural parameter, column 3 reports the model-implied wage variance by imposing all the parameters to be in period 1, but the parameter(s) of interest being at period 2 level. The predictions arising from this estimation, considering industry-heterogeneous pattern in the substitutability of factors of production suggest that, in order to account for trends in industry-level US wage inequality across routine workers a pivotal role is played by* σ *only. In fact, while unique changes in* ρ *would have determined a negligible level of between-industry routine wage variance (.35), changes in the parameter governing the routine-non routine labour force substitution*

(σ) would imply a closer magnitude (.99) to that in the data. Given these opposite effects, and considering both shifts, then the implied real $\log$-wage variance for routine workers (.66) is just an average of the single effects. Column 5 quantifies the importance of each parameter in explaining the observed trend in US routine wage inequality since it shows the share of the model real $\log$-wage variance implied by shift in parameter(s) in the empirical data variance. Heterogeneous shifts in both elasticities are able to capture more than a half (58%) of the data-implied level of the routine task between-industry wage variance (70% of the full calibrated model for the second period, 2013-2022). These findings suggest that, for routine workers, major wage differentials among industries are due to different and industry-heterogeneous degrees of substitution between routine and non-routine labour force, with a mitigating role for that between non-routine workers and ICT capital. Above conclusions directly bridge to the interpretation of changes in θ, whose value shifts from $\theta_{\text{2003-2012}} = 7.26$ to $\theta_{\text{2013-2022}} = 7.79$; alone, stronger labour market concentration measured by such positive shift would slightly lowered routine real $\log$-wage variance (.57) but, when such reduction in households' productivity dispersion is accompanied by an heterogeneous pattern of the elasticities of substitution as suggested by Table 7, its effect would increase the explained economy-wide between-routine workers wage inequality across industries; put it differently, given heterogeneous changes in substitutability parameters' degrees, a highly concentrated labour market induced by stronger industry-level sorting and segregation effects increases routine task inequality in labour income. Considering only variations in industry-specific structural characteristics (through simultaneous changes in both elasticities of substitution) in combination with those in the labour market resilience (as measured by sorting and segregation effects via workers' concentration), the model predicts that the component $\Delta(\sigma, \rho, \theta)$ is able to explain 63% of the data-implied industry-level US variance of real $\log$-wages across routine workers.

On the other hand in the lower part of the table I conjecture what would have been the routine variance if only a specific parameter is fixed at its initial level, letting the remaining parameters free to change from period 1 to period 2.[VI] *Absent any changes in σ – thus giving a first order role to the combination of changes in ρ and θ with that of the weights and income shares in the production function, heterogeneous across industries –, accounted routine workers variance would have been closer to the actual in the data explaining 62% of the occurred trend, while fixing the combination of the two elasticities $\left(\Delta\Theta_{|(\sigma,\rho)}\right)$, explained variance would have been lower (.84) to the actual variance in both data and model; similar result (.81) is found when fixing all the parameters of interest (thus considering only the role played by income shares, α, μ and λ), namely (σ, ρ, θ). Finally, keeping constant the households' productivity dispersion parameter (θ), thus letting the two elasticities and the other*

[VI] *Important remark*: this counterfactual analysis, differently from the upper part of Table C.11, allows to consider also changes in the production function weights, which are industry-specific too. In other words, this exercise considers both changes in structural parameters $(\rho_s, \sigma_s)_{\forall s}$ and in production parameters $(\alpha_s, \mu_s, \lambda_s)_{\forall s}$, besides the usual change in households' productivity dispersion measured by shifts in θ.

industry-specific parameters to vary, a substantial share of the routine workers variance would have been explained: considering only industry-heterogeneous changes in both the substitution-elasticities and the weighting parameters, a share of 79% of the data-implied industry-level US variance of real $\log$-wages across routine workers can be explained (accounting for 95% in the model).

TABLE C.12: MODEL COUNTERFACTUALS FOR NON-ROUTINE WORKERS

		Δ ***model*** $\vert\ \Delta\ m\Big(\Phi(x,\tau_2),\Theta=\{p_{\tau_2},-p_{\tau_1}\}\Big)$		
non-routine wages	$var(w)_{\tau_2}$	*level*	*share, model*	*share, data*
CHANGE				
DATA	1.21			
MODEL	1.22			
$\Delta\sigma$		3.74	3.06	3.09
$\Delta\rho$		1.41	1.15	1.16
$\Delta(\sigma,\rho)$		1.57	1.28	1.30
$\Delta\theta$		2.11	1.73	1.75
$\Delta(\sigma,\rho,\theta)$		1.61	1.31	1.33
FIXING				
DATA	1.21			
MODEL	1.22			
$\Delta\Theta_{\vert\sigma}$		1.16	.95	.96
$\Delta\Theta_{\vert\rho}$		3.27	2.67	2.70
$\Delta\Theta_{\vert(\sigma,\rho)}$		1.78	1.45	1.47
$\Delta\Theta_{\vert\theta}$		1.18	.97	.98
$\Delta\Theta_{\vert(\sigma,\rho,\theta)}$		1.79	1.46	1.48

Quantification of Model A and Model B. Model implied industry-level between-non-routine workers real $\log$-wage variance changes between two time spans differently calibrated, and changes also according to variations in some parameters; values are referred to variance levels considering bottom, middle, and top industries. Column 2 shows the level in the second period of the between-industry variance both in the data and in the period-two fully calibrated model. For the model specified in column 1: column 3 represents the variance level in the second period as implied by the change in the parameter(s), while column 4 computes the second period variance share of the period-two full model which is accounted by the change in a specified parameter, $\frac{m\left[\Phi(x,\tau_2)\,\middle|\,\Theta(p,\tau_2),\Theta(-p,\tau_1)\right]}{m\left[\Phi(x,\tau_2)\,\middle|\,\Theta(p,\tau_2)\right]}$, where $\Phi(x,\tau_2)$ identifies the series in the second period, and Θ the set of parameters where some of them, (p,τ_2), are taken in the second period, while $(-p,\tau_1)$ reflects the set of all the parameters in the first period but those considered in the second period. Column 5 reports the fraction of variance explained by changes in parameter(s) in the observed data-driven variance.

(Comment for non-routine workers) *Results for non-routine workers are reported in Table C.12. Second column shows the between-industry real $\log$-wage variance for non-routine workers only related to second period (p_2) both in the data and in the model specified in column 1. Changing one or more parameters at a time, to evaluate the role of each structural parameter, column 3 reports the model-implied wage variance by imposing all the parameters to be in period 1, but the parameter(s) of interest* *being at period 2 level. The predictions arising from this estimation, considering industry-heterogeneous pattern in the substitutability of factors of production suggest that, in order to account for trends in industry-level US wage inequality across non-routine workers a pivotal role is played by σ, and thus by observed changes in the substitution effect between routine and non-routine workers. In fact, while unique changes in ρ would have determined a substantial level of between-industry non-routine wage variance (1.41), larger impact is devoted to changes in the parameter governing the routine-non routine labour force substitution: alone, industry-specific changes in σ would have rather implied a massive level of wage dispersion (3.74). Given these opposite-in-size effects, and considering both shifts, then the implied real $\log$-wage variance for non-routine workers (1.57) would have been closer to that implied by the full calibration model. Column 5 quantifies the importance of each parameter in explaining the observed trend in US wage inequality since it shows the share of the model real $\log$-wage variance implied by shift in parameter(s) in the empirical data variance. Heterogeneous shifts in both elasticities are able to capture 130% of the data-implied level of between-industry non-routine tasks wage variance (128% of the full calibrated model for the second period, 2013-2022). These findings suggest that major wage differentials among industries are due to different and industry-heterogeneous degrees of substitution between non-routine workers and ICT capital, rather than the degree of substitution between routine and non-routine labour force. Above conclusions directly bridge to the interpretation of changes in θ, whose value shifts from $\theta_{2003\text{-}2012} = 7.26$ to $\theta_{2013\text{-}2022} = 7.79$; alone, stronger labour market concentration measured by such positive shift would mostly surge non-routine real $\log$-wage variance (2.11) but, when such reduction in households' productivity dispersion is accompanied by an heterogeneous pattern of the elasticities of substitution as suggested by Table 7, its effect would slightly inflate the explained economy-wide non-routine workers wage inequality across industries; put it differently, given heterogeneous changes in substitutability parameters' degrees, a highly concentrated labour market induced by stronger worker types' sorting and segregation factors increases overall non-routine task inequality in labour income. Considering only variations in industry-specific structural characteristics (through simultaneous changes in both elasticities of substitution) in combination with those in the labour market resilience (as measured by sorting and segregation effects via workers' concentration), the model predicts that the component $\Delta(\sigma, \rho, \theta)$ is able to explain 133% of the data-implied industry-level US variance of real $\log$-wages across non-routine workers.*

On the other hand in the lower part of the table I conjecture what would have been the non-routine variance if only a specific parameter is fixed at its initial level, letting the remaining parameters free to change from period 1 to period 2.[VII] *Absent any changes in σ – thus giving a first order role to the combination of changes in ρ and θ*

[VII] *Important remark*: this counterfactual analysis, differently from the upper part of Table C.12, allows to consider also changes in the production function weights, which are industry-specific too. In other words, this exercise considers both changes in structural parameters $(\rho_s, \sigma_s)_{\forall s}$ and in production parameters $(\alpha_s, \mu_s, \lambda_s)_{\forall s}$, besides the usual change in households' productivity dispersion measured by shifts in θ.

with that of the weights and income shares in the production function, heterogeneous across industries –, accounted non-routine workers variance would have been closer to the actual in the data explaining 96% of the occurred trend, while fixing the combination of the two elasticities $\left(\Delta\Theta_{|(\sigma,\rho)}\right)$*, explained variance would have been notably higher (1.78) to the actual variance in both data and model; similar result (1.79) is found when fixing all the parameters of interest (thus considering only the role played by income shares,* α*,* μ *and* λ*), namely* (σ,ρ,θ)*. Finally, keeping constant the households' productivity dispersion parameter* (θ)*, thus letting the two elasticities and the other industry-specific parameters to vary, almost all of the non-routine workers variance would have been explained: considering only industry-heterogeneous changes in both the substitution-elasticities and the weighting parameters, a share of 98% of the data-implied industry-level US variance of real* $\log$*-wages across non-routine workers can be explained (accounting for 97% in the model).*

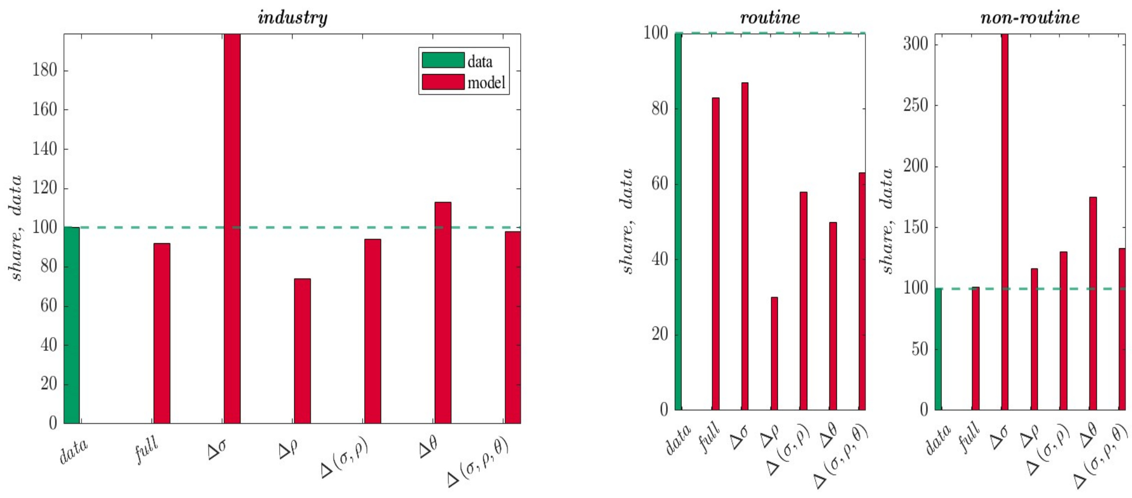
(Comparative comment) *Investigations on the contribution of structural parameters outline an important feature of the US wage structure: observed structural differences among industries account for a sizeable fraction of wage inequality. All the effects can be summarized as follows:*

(a) ***routines****. Most of the share is accounted by trends in industry-heterogeneous differentials in elasticities of substitution among capital and worker types (58%, upper part of Table C.11), also taken in combination to different weights of factor inputs in production (79%, lower part of Table C.11). Considering these differences across industries, the rise in labour market concentration in terms of workers' complementarities (sorting and segregation effects) is an amplifier of US wage inequality across routine job tasks in the last two decades, explaining 63% of the total between-industry routine real $\log$-wage variance (upper part of Table C.11);*

(b) ***non-routines****. Most of the share is accounted by trends in industry-heterogeneous differentials in elasticities of substitution among capital and worker types (130%, upper part of Table C.12), also taken in combination to different weights of factor inputs in production (98%, lower part of Table C.12). Considering these differences across industries, the rise in labour market concentration in terms of workers' complementarities (sorting and segregation effects) is an amplifier of US wage inequality across non-routine job tasks in the last two decades, explaining 133% of the total between-industry non-routine real $\log$-wage variance (upper part of Table C.12);*

(c) ***industries****. Most of the share is accounted by trends in industry-heterogeneous differentials in elasticities of substitution among capital and worker types (94%, Table 8), also taken in combination to different weights of factor inputs in production (88%, Table C.10). Considering these differences across industries, the rise in labour market concentration in terms of workers' complementarities (sorting and segregation effects) is a amplifier of US wage inequality across industries in the last two decades, explaining 98% of the total between-industry real $\log$-wage variance (Table 8).*

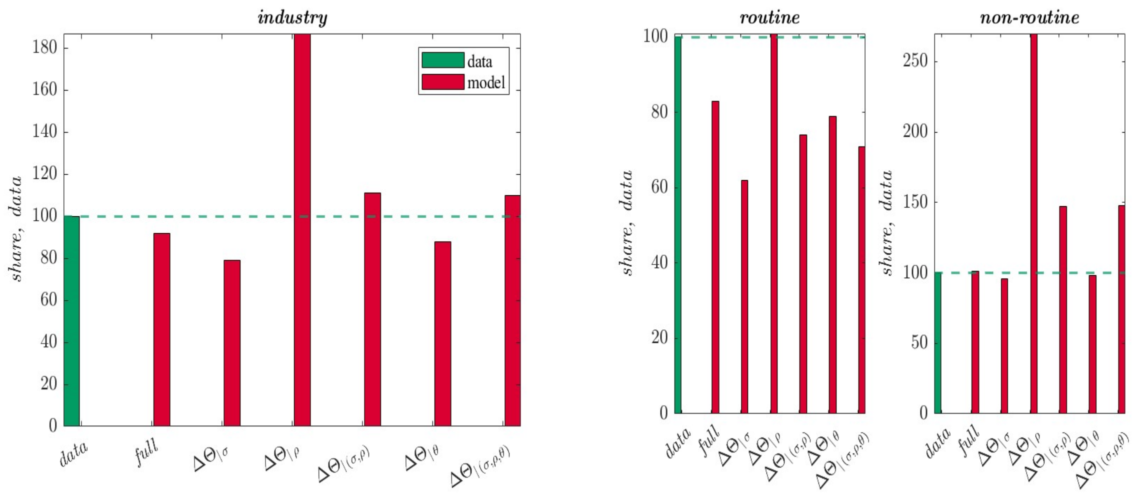
Under a comparative perspective, routine workers wage inequality behaves similarly from that of non-routine and industries. All these variances are mostly explained by the substitution elasticity between routine and non-routine workers (σ) *only and, jointly, the huge negative effect of* σ *on wage inequality is reduced due to changes in* ρ*. On the role of* θ*, again a clear division does not emerge: real wage dispersion increases after an increase in labour market concentration either for routine and non-routine workers and for industries. Henceforth, stronger workers' complementarities through stronger sorting and segregation effects result in negatively impacting all the considered categories, thus increasing real* $\log$*-wage dispersion.*



(A) INDUSTRY (B) TASKS

FIGURE C.12: MODEL COUNTERFACTUAL, CHANGE

Note: these figures plot the second-period between-industry real *log*-wage variance, as a share of that in the data, implied by the model when changing one or more parameters at time as shown in Table 8 and in the upper part of Tables C.11 and C.12, for industry (total employment), routine and non-routine workers.



(A) INDUSTRY (B) TASKS

FIGURE C.13: MODEL COUNTERFACTUAL, FIXING

Note: these figures plot the second-period between-industry real *log*-wage variance, as a share of that in the data, implied by the model when fixing one or more parameters at time as shown in Table C.10 and in the lower part of Tables C.11 and C.12, for industry (total employment), routine and non-routine workers.

(Comment for Skill-Biased Technological Change (SBTC) estimation) *As argued in the main text, Section 4.3, Skill-Biased Technological Change (SBTC) theory implies that wage differentials are shaped by different adoption rate of technology, so that dispersion in wages is mostly affected by how much an industry increases its technological capital and this, in turn, will increase its demand for high-skill or non-routine workers. Thus, below I have performed an exercise where the main structural parameters in the model, namely* $(\rho_s, \sigma_s, \theta)_{\forall s \in \{bot,mid,top\}}$, *and the production function weighting parameters, namely* $(\alpha_s, \mu_s, \lambda_s)_{\forall s \in \{bot,mid,top\}}$, *are keeping fixed at the first period, and let to change the series related to routine and non-routine workers, and that of ICT capital, as described in the main text by Model C; the output of such exercise is shown in Table C.13.*

The analysis performed is conducted by considering industries as a whole, that is, keeping the total employment in terms of both routine and non-routine workers, in order to address the determinants of between-industry wage inequality. As noticed, these two exercises can be performed also by distinguish the effects of changing parameters on separate job tasks; to this end, Table C.14 reports the SBTC analysis for both routine and non-routine workers. The impact of SBTC seems to have major effect on non-routine workers: in fact, while the variance explained by shifts in the series explain substantially less data-share compared to the case in which shifts in structural parameters are also considered, the wage variance of non-routine workers explodes. Therefore, as in the model, major impact of only the series is on non-routine workers.

TABLE C.13: MODEL COUNTERFACTUAL, SBTC

		Δ ***model*** $\mid \Delta\, m\Big(\Phi = \{x_{\tau_2}, -x_{\tau_1}\} \;\Big|\; \Theta(p,\tau_1)\Big)$		
industry wages	$var(w)_{\tau_2}$	*level*	*share, model*	*share, data*
DATA	1.18			
MODEL	1.09			
$\Delta\ell(rt)$		2.62	2.42	2.22
$\Delta\ell(nrt)$		.35	.32	.29
$\Delta\ell$		1.32	1.22	1.12
$\Delta k(ict)$		1.99	1.84	1.69
$\Delta(\ell, ict)$		1.34	1.23	1.13

Quantification of Model C. Model implied between-industry real log-wage variance changes between two time spans uniformly calibrated, with changes according to variations in some series; values are referred to variance levels considering bottom, middle, and top industries. Column 2 shows the level in the second period of the between-industry variance both in the data and in the period-two fully calibrated model. For the model specified in column 1: column 3 represents the variance level in the second period as implied by the change in the parameter(s), while column 4 computes the second period variance share of the period-two full model which is accounted by the change in a specified parameter, $\frac{m\left[\Phi(x,\tau_2),\Phi(-x,\tau_1)\,\middle|\,\Theta(p,\tau_1)\right]}{m\left[\Phi(x,\tau_2)\,\middle|\,\Theta(p,\tau_2)\right]}$, *where* $\Theta(x,\tau_1)$ *identifies the set of parameters in the first period, and* Φ *the set of capital and labour series where some of them,* (x,τ_2), *are taken in the second period, while* $(-x,\tau_1)$ *reflects the set of all the series in the first period but those considered in the second period. Column 5 reports the fraction of variance explained by changes in parameter(s) in the observed data-driven variance.*

TABLE C.14: MODEL COUNTERFACTUAL, SBTC BY TASKS

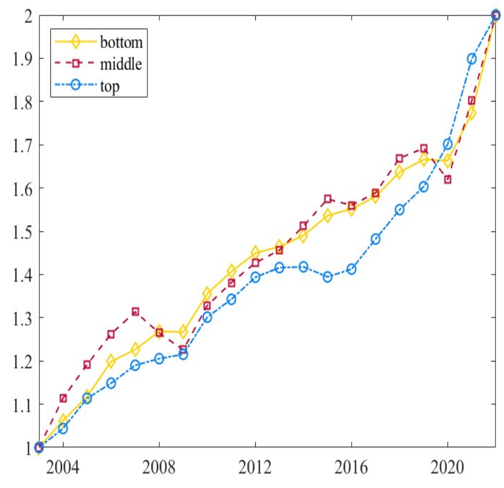
wages	$var(w)_{\tau_2}$	Δ ***model*** $\mid \Delta\, m\Big(\Phi = \{x_{\tau_2}, -x_{\tau_1}\} \Big\vert \Theta(p,\tau_1)\Big)$ *level*	*share, model*	*share, data*
		ROUTINE		
DATA	1.14			
MODEL	.95			
$\Delta\ell(rt)$		1.21	1.28	1.06
$\Delta\ell(nrt)$		.20	.21	.18
$\Delta\ell$		.56	.59	.49
$\Delta k(ict)$		.86	.91	.75
$\Delta(\ell, ict)$		.53	.56	.47
		NON-ROUTINE		
DATA	1.21			
MODEL	1.22			
$\Delta\ell(rt)$		4.04	3.30	3.34
$\Delta\ell(nrt)$		.50	.40	.41
$\Delta\ell$		2.09	1.70	1.73
$\Delta k(ict)$		3.13	2.56	2.59
$\Delta(\ell, ict)$		2.14	1.75	1.77

Quantification of Model C for routine and non-routine workers separately. Model implied between-industry real log-wage variance changes between two time spans uniformly calibrated, with changes according to variations in some series; values are referred to variance levels considering bottom, middle, and top industries. Column 2 shows the level in the second period of the between-industry variance both in the data and in the period-two fully calibrated model. For the model specified in column 1: column 3 represents the variance level in the second period as implied by the change in the parameter(s), while column 4 computes the second period variance share of the period-two full model which is accounted by the change in a specified parameter, $\frac{m\left[\Phi(x,\tau_2),\Phi(-x,\tau_1)\,\middle\vert\,\Theta(p,\tau_1)\right]}{m\left[\Phi(x,\tau_2)\,\middle\vert\,\Theta(p,\tau_2)\right]}$*, where* $\Theta(x,\tau_1)$ *identifies the set of parameters in the first period, and* Φ *the set of capital and labour series where some of them,* (x,τ_2)*, are taken in the second period, while* $(-x,\tau_1)$ *reflects the set of all the series in the first period but those considered in the second period. Column 5 reports the fraction of variance explained by changes in parameter(s) in the observed data-driven variance.*

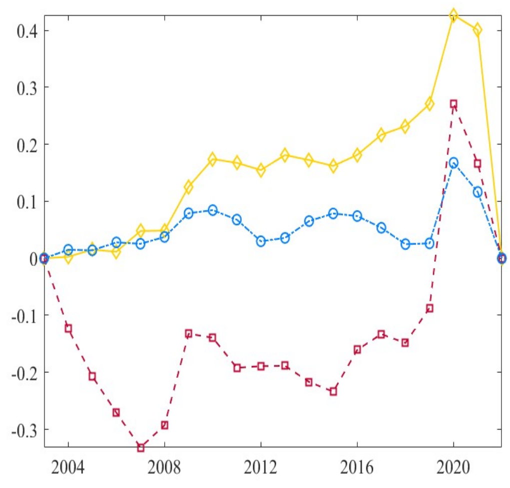
TABLE C.15: MODEL VS. DATA COUNTERFACTUAL, SERIES

		model $\mid \Delta\,\Phi(x)$						
							$\Delta\,(tfp)$	
	data	$\Delta\ell(rt)$	$\Delta\ell(nrt)$	$\Delta\ell$	$\Delta k(ict)$	$\Delta\,(\ell, ict)$	*newly*	*baseline*
WAGES, VARIANCE								
routine	2.285	.62	.41	.46	.54	.40	.57	.34
non-routine	2.314	.07	.02	.02	.04	.03	.02	.09
industry	2.299	.35	.22	.24	.29	.21	.30	.22

Quantification of Model D. Changes in variances in real log*-wages in the model induced by variations in one or more series, keeping fixed the others, and imposing the newly estimated parameters to be homogeneous across industries.* $\Delta\,(\ell)$ *refers to joint variations in routine and non-routine series,* $\Delta\,(tech)$ *is associated to simultaneous changes in both ICT capital and non-routine workers, while changes in estimated industry-specific Hicks-neutral exogenous total factor productivity (TFP), given eq. (14), are captured by* $\Delta\,(tfp)$*; TFP series are taken under the same (newly estimated) parameters' values, or given the baseline calibration (Table 3.2). In all the columns, the variation is computed throughout the period-by-period percentage differential thus identifying overall changes in empirical trends implied both by the data and the model; same values differ in terms of decimals.*



(A) UNIQUE CALIBRATION, NEWLY



(B) DIFFERENCE WITH BASELINE

FIGURE C.14: ESTIMATED PRODUCTIVITIES

Note: this figure shows the estimated Hicks-neutral exogenous total factor productivity (TFP) measures estimated from the model. Panel (a) plots the series given a calibration where all the parameters are evenly set at the same *newly estimated* values for all the industry-groups, while Panel (b) shows the difference between such series and the estimated TFP measures using the baseline calibration reported in Table 4. Series are scaled to be in the same range for graphical comparison.

D. Case under monopsony power

(Discussion) *In this appendix I am going to replicate all the analysis in the main text (calibration, estimation and counterfactuals) under the case in which firms are assumed to be monopolistically competitive and take the labour supply of each task-a as given. In this case, frictions due to a concentration in the labour market suggest that wages' formation is decided at firm level so that, taking labour supplies and industry variables as given, the profit-maximization problem for firm-h in industry-s becomes*

$$\max_{p_h(s),k_h(j,s),w_h(a,s)} \left[\mathcal{D}_h(s) \mid y_h(s), \ell_h(a,s)\right]$$

where firms have wage-setting power over employees. In other words, the profit maximization implies that the Cobb Douglas-nested CES production function in eq. (9) is subject to the labour supply curves specified by eq. (6), and to the conditional firm demand in eq. (8), thus exploiting both monopolistic and monopsonistic power, respectively, in combination. Optimality conditions are shown in Appendix B. As you will notice, whether one decides to assume or not a monopsony power by the part of firms (i.e., maximizing taking $\ell_h(a,s)$ as a constraint) does not change substantially the results and the conclusion of the main text. In fact, the only difference between optimal wages for routine and non-routine workers for a monopsonistic-monopolistically competitive firms in eq. (10) and that of a monopolistically competitive firm only in eq. (D.1) is just the wage-markdown element $\mathcal{M}^\theta = \frac{\theta}{1+\theta}$ in both the composite parameters $\chi(a,s)$, a feature of firms when considering also a monopsonistic environment.

Since θ, measuring the degree of sorting and segregation effects in the economy, is the same for all industries, changes in variances due to changes in θ have an even effect in each industries, thus not changing the conclusion of the main text. This is because, as already noticed, the specification of the households' sorting choices comprises in itself the definition of monopsony power since the measure of workers of type-a in firm-h, industry-s is mostly determined by relative wages as in eq. (6).

Below there is the entire derivation of the firm/industry problem under the assumption of an even monopsony power by the part of firms, while further below it is reported the full analysis (i.e., calibration results and counterfactual exercises) under the monopsony assumption.

(Firm optimization under monopolistic competition and monopsony power) *Given $y_h(s)$ being the production function in eq. (9), the firm's conditional demand of eq. (8), and labour supplies of each task-a all determined by eq. (6), the problem of a monopsonistic-monopolistically competitive firm (h,s) is*

$$\max_{p_h(s),\{k_h(j,s)\}_{\forall j},\{w_h(a,s)\}_{\forall a}} p_h(s)y_h(s) - \left(\sum_j R(j)\, k_h(j,s) \;+ \sum_a w_h(a,s)\, \ell_h(a,s)\right)$$

$$s.t. \quad y_h(s) = \left(\frac{p_h(s)}{p(s)}\right)^{\epsilon} y(s) \quad and \quad \ell_h(a,s) = \left(\frac{w_h(a,s)}{\mathcal{W}_{\mathcal{H}}(a,\mathcal{S})}\,\frac{\mathcal{B}_h(a,s)}{\mathcal{B}_{\mathcal{H}}(a,\mathcal{S})}\right)^{\theta}$$

with $a = \{rt, nrt\}$ and $j = \{phy, ict\}$. Substituting out each $\ell_h(a,s)$, the inter-temporal Lagrangian function for firm-h industry-s takes the form of

$$\begin{aligned}
\underset{p_h(s),\{k_h(j,s),w_h(a,s)\}_{\forall j,a}}{\mathcal{L}} &= p_h(s)y_h(s) - \Big(R(phy)\, k_h(phy,s) + R(ict)\, k_h(ict,s) + \\
&\quad + w_h(rt,s)\, \ell_h(rt,s) + w_h(nrt,s)\, \ell_h(nrt,s)\Big) + \\
&\quad - \psi^t \Big[y_h(s) p_h(s)^{\epsilon} - y(s)\Big]
\end{aligned}$$

with ψ^t being the penalty multiplier. Optimality conditions are in order

$$\begin{aligned}
\frac{\partial \mathcal{L}}{\partial p_h(s)} &: \; \psi = \frac{1}{\epsilon} p_h(s)^{1-\epsilon} \\
\frac{\partial \mathcal{L}}{\partial k_h(phy,s)} &: \; p_h(s) f_{k_h(phy,s)} = \mathcal{M}R(phy) \\
\frac{\partial \mathcal{L}}{\partial k_h(ict,s)} &: \; p_h(s) f_{k_h(ict,s)} = \mathcal{M}R(ict)
\end{aligned}$$

with the price mark-up being

$$\mathcal{M} = \frac{\epsilon}{\epsilon - 1}$$

and first order conditions of firm-industry specific output relative to capital-types are

$$\begin{aligned}
F_{k_h(phy,s)} &= \alpha \Big(k_h(phy,s)\Big)^{\alpha-1} \left[y_h(s)\Big(k_h(phy,s)\Big)^{-\alpha}\right] \\
F_{k_h(ict,s)} &= (1-\alpha)(1-\mu)\lambda \left[\Big(k_h(phy,s)\Big)^{\alpha} \mathcal{V}_h^{\frac{1-\alpha-\varsigma}{\varsigma}} \mathcal{Q}_h^{\frac{\varsigma-\varrho}{\varrho}}\right] \Big(k_h(ict,s)\Big)^{\varrho-1}
\end{aligned}$$

with

$$\mathcal{V}_h = \mu\Big(\ell_h(rt,s)\Big)^{\varsigma} + (1-\,\mu)\, \mathcal{Q}_h^{\frac{\varsigma}{\varrho}}$$

and

$$\mathcal{Q}_h = \lambda\Big(k_h(ict,s)\Big)^{\varrho} + (1-\lambda)\Big(\ell_h(nrt,s)\Big)^{\varrho}$$

Note how aggregate capital rental rates, $R_t\,(j)$, are obtained by aggregating marginal product of capital types $\left(f_{k_h(j,s)}\right)$ across firms and industries.

Optimality conditions for wages are found by deriving for $w_h(a,s)$ instead of $\ell_h(a,s)$ if one imposes monopsony power of firms in the labour market when exploiting eq. (6). This results in computing what follows.

$$\frac{\partial\mathcal{L}}{\partial w_h(rt,s)} \;:\; p_h(s)f_{w_h(rt,s)} = \mathcal{M}(1+\theta)\ell_h(rt,s)$$

$$\frac{\partial\mathcal{L}}{\partial w_h(nrt,s)} \;:\; p_h(s)f_{w_h(nrt,s)} = \mathcal{M}(1+\theta)\ell_h(nrt,s)$$

with the price mark-up still being $\mathcal{M} = \frac{\epsilon}{\epsilon-1}$, and first order conditions of firm (h,s)'s output relative to labour-types are

$$f_{w_h(rt,s)} = (1-\alpha)\mu\theta\Big(k_h(phy,s)\Big)^{\alpha}\mathcal{V}_h^{\frac{1-\alpha-\varsigma}{\varsigma}}$$
$$\left(\frac{\Big(w_h(rt,s)\mathcal{B}_h(rt,s)\Big)^{\theta}}{\Big(\sum_{h,s} w_h(rt,s)\mathcal{B}_h(rt,s)\Big)^{\theta}}\right)^{\varsigma-1}\frac{w_h(rt,s)^{\theta-1}\mathcal{B}_h(rt,s)^{\theta}}{\Big(\sum_{h,s} w_h(rt,s)\mathcal{B}_h(rt,s)\Big)^{\theta}}$$

$$f_{w_h(nrt,s)} = (1-\alpha)(1-\mu)(1-\lambda)\theta\Big(k_h(phy,s)\Big)^{\alpha}\mathcal{V}_h^{\frac{1-\alpha-\varsigma}{\varsigma}}\mathcal{Q}_h^{\frac{\varsigma-\varrho}{\varrho}}$$
$$\left(\frac{\Big(w_h(nrt,s)\mathcal{B}_h(nrt,s)\Big)^{\theta}}{\Big(\sum_{h,s} w_h(nrt,s)\mathcal{B}_h(nrt,s)\Big)^{\theta}}\right)^{\varrho-1}\frac{w_h(nrt,s)^{\theta-1}\mathcal{B}_h(nrt,s)^{\theta}}{\Big(\sum_{h,s} w_h(nrt,s)\mathcal{B}_h(nrt,s)\Big)^{\theta}}$$

with

$$\mathcal{V}_h = \mu\Big(\ell_h(rt,s)\Big)^{\varsigma} + (1-\mu)\,\mathcal{Q}_h^{\frac{\varsigma}{\varrho}}$$

and

$$\mathcal{Q}_h = \lambda\Big(k_h(ict,s)\Big)^{\varrho} + (1-\lambda)\Big(\ell_h(nrt,s)\Big)^{\varrho}$$

By writing down the extensive forms for each derivative of $w_h(a,s)$ and exploiting the calculations, together with proposition 1, optimal wages at industry-s level are, respectively, given by

$$w(rt,s) = \left[\Lambda(s)\,\chi(rt,s)\,\left(k(phy,s)\right)^{\alpha}\,\mathcal{V}^{\frac{1-\alpha-\varsigma}{\varsigma}}\,\left(\frac{\mathcal{B}(rt,s)}{\mathcal{WB}(rt,\mathcal{S})}\right)^{\theta(\varsigma-1)}\right]^{\frac{1}{1+\theta-\theta\varsigma}}$$

$$w(nrt,s) = \left[\Lambda(s)\,\chi(nrt,s)\,\left(k(phy,s)\right)^{\alpha}\,\mathcal{V}^{\frac{1-\alpha-\varsigma}{\varsigma}}\,\mathcal{Q}^{\frac{\varsigma-\varrho}{\varrho}}\,\left(\frac{\mathcal{B}(nrt,s)}{\mathcal{WB}(nrt,\mathcal{S})}\right)^{\theta(\varrho-1)}\right]^{\frac{1}{1+\theta-\theta\varrho}} \tag{D.1}$$

which are exactly the same conditions of eq. (10) with the only difference that now composite parameters are defined as $\chi(rt,s) = (1-\alpha)\mu\mathcal{M}^{\theta}$ *and* $\chi(nrt,s) = (1-\alpha)(1-\mu)(1-\lambda)\mathcal{M}^{\theta}$, $\Lambda(s) = p(s)\,\mathcal{M}^{-1}$ *is an indicator combining the industry-specific price level multiplied by the price mark-up, and* $\mathcal{WB}(a,\mathcal{S}) = \sum_s \mathcal{W}_{\mathcal{H}}(a,s)\mathcal{B}_{\mathcal{H}}(a,s)$. *Aggregate industry wage is thus found by averaged aggregation:* $w(s) = (\mathcal{A})^{-1}\sum_a w(a,s)$. *Note that* $\mathcal{V}_h$ *expresses the substitutability between routine workers* $\left(\ell_h(rt,s)\right)$ *and the ICT composite good* $\left(\mathcal{Q}_h\right)$, *while* $\mathcal{Q}_h$ *identifies the substitutability between ICT capital* $\left(k_h(ict,s)\right)$ *and non-routine workers* $\left(\ell_h(nrt,s)\right)$, *considering each firm* $h \in \mathcal{H}$ *in industry-*s.

Element $\mathcal{M}^{\theta} = \frac{\theta}{(1+\theta)}$ *is the wage markdown arising from the wage-setting behaviour of firms having monopsony power. It is increasing in the level of labour supply elasticity: as* $\theta \to \infty$, *households' productivities are becoming less and less dispersed and the labour supply elasticity is lower, so that monopsony power increases as well as the wage markdown. On the contrary, as* $\theta \to 1$ *households' productivities are more dispersed and the labour supply elasticity is higher, so that monopsony power decreases as well as the wage markdown. An important remark is that the difference between the case of a monopsonistic and monopolistically competitive firm and that with a monopolistically competitive firm only (main text) is the entity of the composite parameter* $\chi(a,s), \forall a$. *In the first case, it comprises the wage markdown term* $\frac{\theta}{1+\theta}$; *however, since* θ *is uneven across industries, the calibration of the parameters is the same of that in Section 3.2, as well as the conclusions of the counterfactual analysis in Section 4.*

Finally, firm (h,s) *profits can be found by including equilibrium optimality conditions for both capital and wages in*

$$\mathcal{D}_h(s) = p_h(s)y_h(s) - \left(\sum_j R(j)k_h(j,s) + \sum_a w_h(a,s)\ell_h(a,s)\right)$$

where $j = \{phy, ict\}$ *identifies the types of capital in the economy.*

(Equilibrium characterization under monopsony) *In equilibrium, the model should specify the clearing conditions of labour, capital, and goods markets. Each* *firm takes from households the labour supply of task $a \in \mathcal{A}$ as measured by eq. (6).*[I] *Aggregating it across tasks and firms results in obtaining the industry-specific labour supply, $L(s) = \sum_{a,h} \ell_h(a,s)$. Analogously, aggregate labour supply of task-a is found by aggregating across firms and industries, $L(a) = \sum_{h,s} \ell_h(a,s)$. It follows that, considering $a = \{rt, nrt\}$, aggregate labour supply for this economy is just $L = \sum_a \sum_h \sum_s \ell_h(a,s) = L(rt) + L(nrt)$. Due to monopsonistic labour market, these quantities also correspond to aggregate, industry, and firm-specific labour demands, so that labour market clears.*

For what concerns equilibrium in the capital market(s), total physical and ICT capital demands from industries are, respectively, $K^D(phy,s) = \sum_h k_h(phy,s)$ and $K^D(ict,s) = \sum_h k_h(ict,s)$, so that aggregate demands are simply determined: $K^D(phy) = \sum_s K^D(phy,s)$ and $K^D(ict) = \sum_s K^D(ict,s)$. By the part of supply, aggregating capital quantities over households would results in aggregate physical and ICT capital supplies: $K^S(phy) = \int_i k^i(phy)\mathrm{d}i$ and $K^S(ict) = \int_i k^i(ict)\mathrm{d}i$. Equilibrium in both markets requires $K(phy) \equiv K^D(phy) = K^S(phy)$ and $K(ict) \equiv K^D(ict) = K^S(ict)$, while market clearing in the capital market implies $K^D(phy) + K^D(ict) = K^S(phy) + K^S(ict)$.

Finally, aggregate profits to be given to households are $\mathcal{D}^D = \int_i \mathcal{D}_i \,\mathrm{d}i$, while $\mathcal{D}^S = \sum_s \mathcal{D}(s)$ are the total profits computed by aggregating industry-specific profits, $\mathcal{D}(s) = \sum_h \mathcal{D}_h(s)$. Equilibrium requires $\mathcal{D} \equiv \mathcal{D}^D = \mathcal{D}^S$. This implies that, by aggregating the households' inter-temporal budget constraints and imposing the clearing conditions so far, including also total quantities for

$$
\begin{aligned}
\mathcal{C}^i &= \int_i \mathcal{C}^i \,\mathrm{d}i \\
I(j) &= \int_i I^i(j)\,\mathrm{d}i\,, \quad \forall j \\
b &= \int_i b^i \,\mathrm{d}i \\
w &= \sum_a \sum_h \sum_s w_h(a,s) \\
\mathcal{B} &= \sum_a \sum_h \sum_s \mathcal{B}_h(a,s)
\end{aligned}
$$

where $\mathcal{B} = 1$ since it is the sum of relative quantities, the aggregate resource constraint for this economy at time t reads as

$$
\mathcal{C}_t + I_t(phy) + I_t(ict) + b_{t+1} - (1+r_t)b_t = w_t \mathcal{B}_t L_t + R_t\Big(K_t(phy) + K_t(ict)\Big) + \mathcal{D}_t
$$

which equals the total output as defined by the final output CES aggregator, Y. Equilibrium conditions are described below.

(Equilibrium under monopsony) *An equilibrium for this economy is defined as*

[I] Since households inelastically supply labour, then it must hold $\ell_h(a,s) = \int_0^1 \ell_h^i(a,s)\mathrm{d}i$.

an households' choice of job place, a combination of factors' prices $\big(w(a,s), R(phy), R(ict)\big)$, *and a set of aggregate quantities* $\Omega = \big\{Y, K(phy), K(ict), L(rt), L(nrt)\big\}$, *such that*

(a) Each household picks the firm-industry tuple that maximizes eq. (4);

(b) According to the occupational choice, each household maximizes its expected-utility version of the utility in eq. (4);

(c) Final and sectoral good producers maximize their revenues;

(d) Given the availability of workers in each job task as in eq. (6), each firm internalizes their own labour demand thus setting optimal wages;

(e) Firms choose also capital bundles to maximize their profits;

(f) All markets clear, shaping Ω.

The steady state consists of an equilibrium in which all variables and changing parameters are constant over time.

TABLE D.1: SUMMARY OF CALIBRATION UNDER MONOPSONY

	parameter	*bottom*	*middle*	*top*	*global*	***source***
		value				
α	*physical capital, share of* $y(s)$	0.263	0.195	0.514		*data*
ϵ	*demand elasticity across firms*				6	*external*
μ	*weight of routine workers in* $y(s)$	0.676	0.490	0.333		*MSM*
λ	*ICT capital share in* $Q(s)$	0.455	0.456	0.439		*MSM*
θ	*households' productivities dispersion*				11.4	*MSM*
ρ	*EoS, ICT capital and non-routine*	0.329	0.420	0.249		*estimation*
σ	*EoS, routine and ICT composite*	0.634	0.400	0.766		*estimation*

Set of estimated parameters of the model. "data" implies that the values are directly computed from data sources, while in "external" I choose standard calibrated values from the literature. "MSM" refers to the Methods of Simulated Moments as in Mc Fadden (1989). "estimation" refers to previously estimated values under a specific procedure; these values are taken from Table 5.

TABLE D.2: METHOD OF SIMULATED MOMENTS UNDER MONOPSONY, RESULTS

	parameter	*value*	***moment to match***	*data*	*model*
				fit	
μ_{bot}	weight of routines in $y(bot)$	0.6760	routine share, bottom	.0858	.1420
μ_{mid}	weight of routines in $y(mid)$	0.4902	routine share, middle	.1357	.1596
μ_{top}	weight of routines in $y(top)$	0.3331	routine share, top	.0985	.0637
λ_{bot}	weight of ICT in $Q(bot)$	0.4552	ICT share, bottom	.3968	.3968
λ_{mid}	weight of ICT in $Q(mid)$	0.4585	ICT share, middle	.3042	.3042
λ_{top}	weight of ICT in $Q(top)$	0.4398	ICT share, top	.2990	.2990
θ	productivity dispersion	11.376	wage premium, $w(a,[s,s'])$	.9945	.9945

Estimated values and related matched moment using the Methods of Simulated Moments by Mc Fadden (1989).

TABLE D.3: MODEL FIT UNDER MONOPSONY, UNTARGETED MOMENTS

	fit	
moment	*data*	*model*
aggregate task-premium	.001	.005
aggregate wage	-.008	-.073
routine wage, bottom	-.016	-.070
routine wage, middle	-.001	-.051
routine wage, top	-.007	-.080
non-routine wage, bottom	-.019	-.060
non-routine wage, middle	.003	-.075
non-routine wage, top	-.010	-.046

Untargeted moments to match to validate the calibration strategy. All moments, referred to real $\log$*-wages, are taken as percentage changes throughout the series.*

TABLE D.4: METHOD OF SIMULATED MOMENTS UNDER MONOPSONY, SPLITTING RESULTS

		2003-2012			**2013-2022**		
	moment to match	*value*	*data*	*model*	*value*	*data*	*model*
μ_{bot}	routine share, bottom	0.225	0.087	0.103	0.415	0.085	0.051
μ_{mid}	routine share, middle	0.492	0.132	0.061	0.506	0.140	0.030
μ_{top}	routine share, top	0.906	0.100	0.013	0.608	0.097	0.083
λ_{bot}	ICT share, bottom	0.647	0.399	0.399	0.786	0.395	0.395
λ_{mid}	ICT share, middle	0.518	0.314	0.314	0.490	0.295	0.295
λ_{top}	ICT share, top	0.170	0.287	0.287	0.326	0.311	0.311
θ	wage premium, $w(a, [s, s'])$	7.255	0.994	0.994	7.787	0.995	0.995

Estimated values and related matched moment using the Methods of Simulated Moments by Mc Fadden (1989).

TABLE D.5: SUMMARY OF CALIBRATION UNDER MONOPSONY, 2003-2012

	parameter	value				source
		bottom	middle	top	global	
α	*physical capital, share of $y(s)$*	0.131	0.091	0.254		*data*
ϵ	*demand elasticity across firms*				6	*external*
μ	*weight of routine workers in $y(s)$*	0.225	0.492	0.906		*MSM*
λ	*ICT capital share in $Q(s)$*	0.647	0.518	0.170		*MSM*
θ	*households' productivities dispersion*				7.26	*MSM*
ρ	*EoS, ICT capital and non-routine*	0.355	0.431	0.408		*estimation*
σ	*EoS, routine and ICT composite*	0.366	0.429	0.367		*estimation*

Set of estimated parameters of the model, first-half of the sample. "data" implies that the values are directly computed from data sources, while in "external" I choose standard calibrated values from the literature. "MSM" refers to the Methods of Simulated Moments as in Mc Fadden (1989). "estimation" refers to previously estimated values under a specific procedure; these values are taken from Table 7.

TABLE D.6: SUMMARY OF CALIBRATION UNDER MONOPSONY, 2013-2022

	parameter	value				source
		bottom	middle	top	global	
α	*physical capital, share of $y(s)$*	0.131	0.104	0.260		*data*
ϵ	*demand elasticity across firms*				6	*external*
μ	*weight of routine workers in $y(s)$*	0.415	0.506	0.608		*MSM*
λ	*ICT capital share in $Q(s)$*	0.786	0.490	0.326		*MSM*
θ	*households' productivities dispersion*				7.79	*MSM*
ρ	*EoS, ICT capital and non-routine*	0.819	0.345	0.508		*estimation*
σ	*EoS, routine and ICT composite*	0.326	0.438	0.357		*estimation*

Set of estimated parameters of the model, second-half of the sample. "data" implies that the values are directly computed from data sources, while in "external" I choose standard calibrated values from the literature. "MSM" refers to the Methods of Simulated Moments as in Mc Fadden (1989). "estimation" refers to previously estimated values under a specific procedure; these values are taken from Table 7.

TABLE D.7: MODEL VS. DATA COUNTERFACTUAL UNDER MONOPSONY, LEVELS

	data	***model***	***model*** $\mid \Delta\, x(j)_{\in\Theta}$				
			$\Delta\sigma$	$\Delta\rho$	$\Delta\,(\sigma,\rho)$	$\Delta\theta$	$\Delta\,(all)$
WAGES, LEVEL ($\Delta_{\%}$)							
routine	-.008	-.067	-.031	-.033	-.031	-.033	-.032
non-routine	-.007	-.061	-.030	-.029	-.029	-.031	-.030
industry	-.007	-.067	-.031	-.032	-.031	-.033	-.031
bottom	-.017	-.065	-.030	-.031	-.030	-.032	-.031
middle	.001	-.070	-.032	-.033	-.031	-.034	-.032
top	-.006	-.065	-.031	-.032	-.031	-.032	-.031
EMPLOYMENT, LEVEL ($\Delta_{\%}$)							
routine	.006	.087	.055	.058	.055	.057	.054
non-routine	.025	.061	.044	.042	.044	.041	.043
industry	.018	.074	.051	.053	.051	.052	.051

Changes in key moments of real log-wages and nominal employment measures in the model induced by an exogenous variation (which is assumed to be homogeneous across groups of industries) in a specific parameter; such shift is computed at the initial period, so that the change identifies the transition from the initial (2003) to the final (2022) steady state level. In the first two columns, the variation is computed throughout the period-by-period percentage differential thus identifying overall changes in empirical trends implied both by the data and the model, while the last three columns are just the percentage difference between the two steady states.

TABLE D.8: MODEL VS. DATA COUNTERFACTUAL UNDER MONOPSONY

	data	***model***	***model*** $\mid \Delta\, x(j)_{\in\Theta}$				
			$\Delta\sigma$	$\Delta\rho$	$\Delta\,(\sigma,\rho)$	$\Delta\theta$	$\Delta\,(all)$
WAGES, VARIANCE							
routine	2.285	2.288	2.31	2.15	2.31	2.20	2.36
non-routine	2.314	2.312	2.29	2.18	2.30	2.20	2.32
industry	2.299	2.300	2.30	2.17	2.30	2.20	2.34

Changes in key moments of real log-wages and nominal employment measures in the model induced by an exogenous variation (which is assumed to be homogeneous across groups of industries) in a specific parameter; such shift is computed at the initial period, so that the change identifies the transition from the initial (2003) to the final (2022) steady state level. In the first two columns, the variation is computed throughout the period-by-period percentage differential thus identifying overall changes in empirical trends implied both by the data and the model, while the last three columns are just the percentage difference between the two steady states.

TABLE D.9: MODEL COUNTERFACTUALS UNDER MONOPSONY

industry wages	$var(w)_{\tau_2}$	Δ ***model*** $\mid \Delta\, m\Big(\Phi(x,\tau_2),\Theta=\{p_{\tau_2},-p_{\tau_1}\}\Big)$ *level*	*share, model*	*share, data*
		CHANGE		
DATA	1.18			
MODEL	1.08			
$\Delta\sigma$		2.36	2.19	1.99
$\Delta\rho$		.88	.82	.75
$\Delta(\sigma,\rho)$		1.12	1.03	.94
$\Delta\theta$		1.34	1.24	1.13
$\Delta(\sigma,\rho,\theta)$		1.16	1.07	.98
		FIXING		
DATA	1.18			
MODEL	1.08			
$\Delta\Theta_{\vert\sigma}$		.94	.87	.79
$\Delta\Theta_{\vert\rho}$		2.21	2.04	1.87
$\Delta\Theta_{\vert(\sigma,\rho)}$		1.31	1.21	1.11
$\Delta\Theta_{\vert\theta}$		1.04	.96	.88
$\Delta\Theta_{\vert(\sigma,\rho,\theta)}$		1.30	1.20	1.10

Quantification of Model A and Model B given both monopsonistic and monopolistic power by the part of firms. Model implied between-industry real log-wage variance changes between two time spans differently calibrated, and changes also according to variations in some parameters; values are referred to variance levels considering bottom, middle, and top industries. Column 2 shows the level in the second period of the between-industry variance both in the data and in the period-two fully calibrated model. For the model specified in column 1: column 3 represents the variance level in the second period as implied by the change in the parameter(s), while column 4 computes the second period variance share of the period-two full model which is accounted by the change in a specified parameter, $\frac{m\left[\Phi(x,\tau_2)\,\middle|\,\Theta(p,\tau_2),\Theta(-p,\tau_1)\right]}{m\left[\Phi(x,\tau_2)\,\middle|\,\Theta(p,\tau_2)\right]}$, *where* $\Phi(x,\tau_2)$ *identifies the series in the second period, and* Θ *the set of parameters where some of them,* (p,τ_2), *are taken in the second period, while* $(-p,\tau_1)$ *reflects the set of all the parameters in the first period but those considered in the second period. Column 5 reports the fraction of variance explained by changes in parameter(s) in the observed data-driven variance.*

Table D.10: Model counterfactuals for routine workers under monopsony

routine wages	$var(w)_{\tau_2}$	Δ ***model*** $\mid \Delta\ m\Big(\Phi(x,\tau_2),\Theta = \{p_{\tau_2}, -p_{\tau_1}\}\Big)$ *level*	*share, model*	*share, data*
		CHANGE		
Data	1.14			
Model	.94			
$\Delta\sigma$		.97	1.03	.85
$\Delta\rho$		.33	.35	.29
$\Delta(\sigma,\rho)$		.64	.68	.57
$\Delta\theta$		.55	.59	.49
$\Delta(\sigma,\rho,\theta)$		.70	.74	.61
		FIXING		
Data	1.14			
Model	.94			
$\Delta\Theta_{\mid\sigma}$		.71	.75	.62
$\Delta\Theta_{\mid\rho}$		1.15	1.22	1.01
$\Delta\Theta_{\mid(\sigma,\rho)}$		.84	.89	.73
$\Delta\Theta_{\mid\theta}$		.89	.95	.78
$\Delta\Theta_{\mid(\sigma,\rho,\theta)}$		.81	.86	.71

Quantification of Model A and Model B given both monopsonistic and monopolistic power by the part of firms. Model implied industry-level between-routine workers real log*-wage variance changes between two time spans differently calibrated, and changes also according to variations in some parameters; values are referred to variance levels considering bottom, middle, and top industries. Column 2 shows the level in the second period of the between-industry variance both in the data and in the period-two fully calibrated model. For the model specified in column 1: column 3 represents the variance level in the second period as implied by the change in the parameter(s), while column 4 computes the second period variance share of the period-two full model which is accounted by the change in a specified parameter,* $\frac{m\left[\Phi(x,\tau_2)\mid\Theta(p,\tau_2),\Theta(-p,\tau_1)\right]}{m\left[\Phi(x,\tau_2)\mid\Theta(p,\tau_2)\right]}$*, where* $\Phi(x,\tau_2)$ *identifies the series in the second period, and* Θ *the set of parameters where some of them,* (p,τ_2)*, are taken in the second period, while* $(-p,\tau_1)$ *reflects the set of all the parameters in the first period but those considered in the second period. Column 5 reports the fraction of variance explained by changes in parameter(s) in the observed data-driven variance.*

TABLE D.11: MODEL COUNTERFACTUALS FOR NON-ROUTINE WORKERS UNDER MONOPSONY

non-routine wages	$var(w)_{\tau_2}$	Δ ***model*** $\mid \Delta\, m\Big(\Phi(x,\tau_2),\Theta=\{p_{\tau_2},-p_{\tau_1}\}\Big)$ *level*	*share, model*	*share, data*
		CHANGE		
DATA	1.21			
MODEL	1.22			
$\Delta\sigma$		3.76	3.08	3.10
$\Delta\rho$		1.44	1.18	1.19
$\Delta(\sigma,\rho)$		1.59	1.30	1.31
$\Delta\theta$		2.12	1.74	1.75
$\Delta(\sigma,\rho,\theta)$		1.63	1.33	1.34
		FIXING		
DATA	1.21			
MODEL	1.22			
$\Delta\Theta_{\mid\sigma}$		1.17	.96	.97
$\Delta\Theta_{\mid\rho}$		3.27	2.68	2.70
$\Delta\Theta_{\mid(\sigma,\rho)}$		1.78	1.46	1.47
$\Delta\Theta_{\mid\theta}$		1.18	.97	.97
$\Delta\Theta_{\mid(\sigma,\rho,\theta)}$		1.79	1.47	1.48

Quantification of Model A and Model B given both monopsonistic and monopolistic power by the part of firms. Model implied industry-level between-non-routine workers real log*-wage variance changes between two time spans differently calibrated, and changes also according to variations in some parameters; values are referred to variance levels considering bottom, middle, and top industries. Column 2 shows the level in the second period of the between-industry variance both in the data and in the period-two fully calibrated model. For the model specified in column 1: column 3 represents the variance level in the second period as implied by the change in the parameter(s), while column 4 computes the second period variance share of the period-two full model which is accounted by the change in a specified parameter,* $\frac{m\left[\Phi(x,\tau_2)\,\middle|\,\Theta(p,\tau_2),\Theta(-p,\tau_1)\right]}{m\left[\Phi(x,\tau_2)\,\middle|\,\Theta(p,\tau_2)\right]}$*, where* $\Phi(x,\tau_2)$ *identifies the series in the second period, and* Θ *the set of parameters where some of them,* (p,τ_2)*, are taken in the second period, while* $(-p,\tau_1)$ *reflects the set of all the parameters in the first period but those considered in the second period. Column 5 reports the fraction of variance explained by changes in parameter(s) in the observed data-driven variance.*

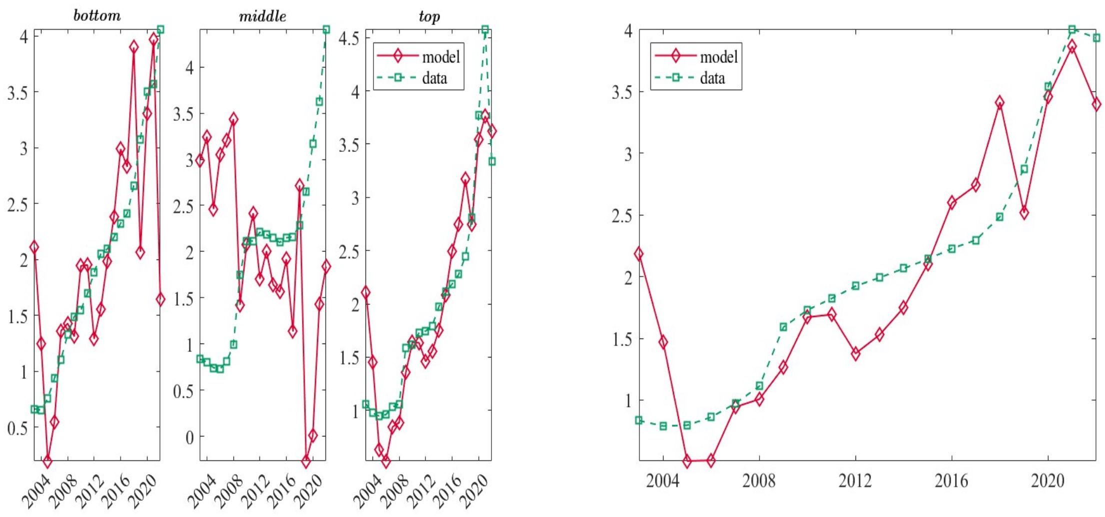
E. On the cyclicality of employment

(Qualitative analysis on fluctuations) *The analysis so far has been focused on explaining the observed trend in US wage inequality which is due to industry factors. However, I would like to conclude with some qualitative considerations on the cyclical behaviour of employment and its relation with wages. Heathcote et al. (2020) argue that the size of the increase in labour income inequality at the top and at the bottom is quite different: dispersion at the top has increased steadily, while that at the bottom features a strong cyclical component.*[I] *The way in which I have built the labour force of each task-s in each firm-h, industry-s, namely eq. (6), is well suited to analyse the evolution of employment combined with that in relative nominal wages once fixing $\mathcal{B}_h(a,s) = 1$, $\forall a, h, s$. Given the presence of not perfectly flexible labour supplies due to sorting and segregation effects, the labour measure I have modelled is entirely determined by a firm's relative wage − relative compared to the industry and aggregate level of wages. Thus, I can directly analyse changes in employment in the data with changes in employment implied by the model, directly linked with changes in industries' relative wage.*

Figure E.1 plots two dynamics for employment: the red square-dot line plots the labour force in the data, while the green solid-diamond line refers to the measure of labour force given the evolution in relative wages associated to the model. Panel E.1b plots the aggregate task ratio for both employment measures. It appears that there is a clear interconnection between relative wages and job tasks substitution, and that the latter is strongly influenced by cyclical fluctuations. Adding more granularity, panel E.1a distinguishes the pattern of the task ratio by specific industry groups. This figure can help even to better understand the results in Section 3.2 in the lights of stylized Fact n. 4 (the "contribution" result): while the dynamics of the task ratio is related to the dynamics of the associated relative wages, it is not so for middle group. In turns this implies that industries which are contributing less to rising wage inequality are not only those without capital-task complementarity (i.e., where $\sigma < \rho$), but also those industries whose substitution of routine workers in the place of non-routines does not follow the associated relative wage premium (relative wage of non-routine over routine tasks). From a cyclical perspective, fluctuations are stronger on wages and, most importantly, there is a negative effect of business cycle on middle industries.

To inspect the aggregate measures of employment, panel E.2a of Figure E.2 shows the pattern of routine and non-routine tasks for both measures (model and data): it strongly appears that routine workers exhibit a strong cyclical pattern, and that this is fairly less cyclical when looking at the routine labour force measured by changes in nominal wages. This suggests that, even if routine workers are those who are highly exposed to fluctuation risks, their relative wage is less subject to business cycle dynamics. Different scenario is for non-routine workers: the steady increase in employment

[I] Authors show that while wage dispersion of those who are at the bottom of the distribution exhibit some business cycle fluctuations (due to cumulative effects of several recessions), those at the top have an increasing trend (mostly driven by changes in their relative wages).



(A) TASK RATIO, BY INDUSTRY-GROUPS

(B) AGGREGATE TASK RATIO

FIGURE E.1: TASK RATIO DYNAMICS

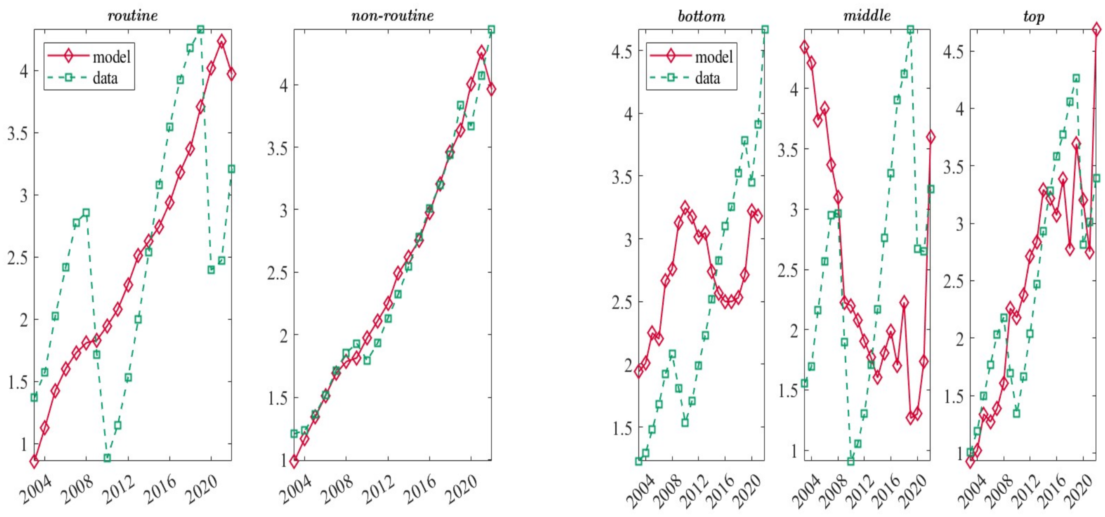
Note: these figures compare the dynamics of the task ratio (non-routine over routine workers) series in the model (solid-red) and in the data (dashed-green). Model-implied employment is defined as in eq. (6), thus measuring employed workforce in terms of industry relative wage. Panel (a) shows the evolution of the task ratio for each subgroup of industries, while Panel (b) plots the aggregate task ratio pattern. Series are scaled to be in the same range for graphical comparison.

is almost entirely associated to increases in relative wages. Even if such dynamics appear to be more exposed to business fluctuations, both employment measures clearly exhibit an upward sloping trend, not a feature of routine workers.

At this point one may wonder which are the industries in which business cycle fluctuations seem to have the wider effects on total employment. The answer lies in panel E.2b, where I plot the total employment by groups of industries. Still, relative wages seem to be the most affected: the model-measure of employment exhibits stronger dependency on fluctuations than the measure in the data. A cross-industry inspection shows that industries in the middle group are those which suffer more from movements in economic activity and, as in the case of the task ratio, these are still affected by a negative effect of fluctuations on wages. In addition, industries located at the top and at the bottom of the industry-wage growth distribution are those which contributed more to inequality (Fact n. 4), as in Table 2. This result is reinforced from the conclusion that middle industries are those which suffer more from the pace of business cycle.

ADDITIONAL FACT (Business cycle) ?? *Routine employment is fluctuating around the economic activity, while it is not the case of their relative wages. More, industries in the middle of the industry-level wage growth distribution are majorly hit by business cycle; this may explain their low contribution to rising wage inequality.*

How these considerations connect with the ongoing debate? First, the presented excursus sheds new lights on the interaction between trend and cycle in explaining US wage inequality: I qualitatively show how it is not enough to consider distinct groups



(A) EMPLOYMENT, BY TASKS

(B) EMPLOYMENT, BY INDUSTRY-GROUPS

FIGURE E.2: EMPLOYMENT DYNAMICS

Note: these figures compare the dynamics of the series in the model (solid-red) and in the data (dashed-green). Model-implied employment is defined as in eq. (6), thus measuring employed workforce in terms of industry relative wage. Panel (a) shows movements in aggregate employment for both routine and non routine workers, while Panel (b) plots the dynamics of total employment of each subgroup of industries. Series are scaled to be in the same range for graphical comparison.

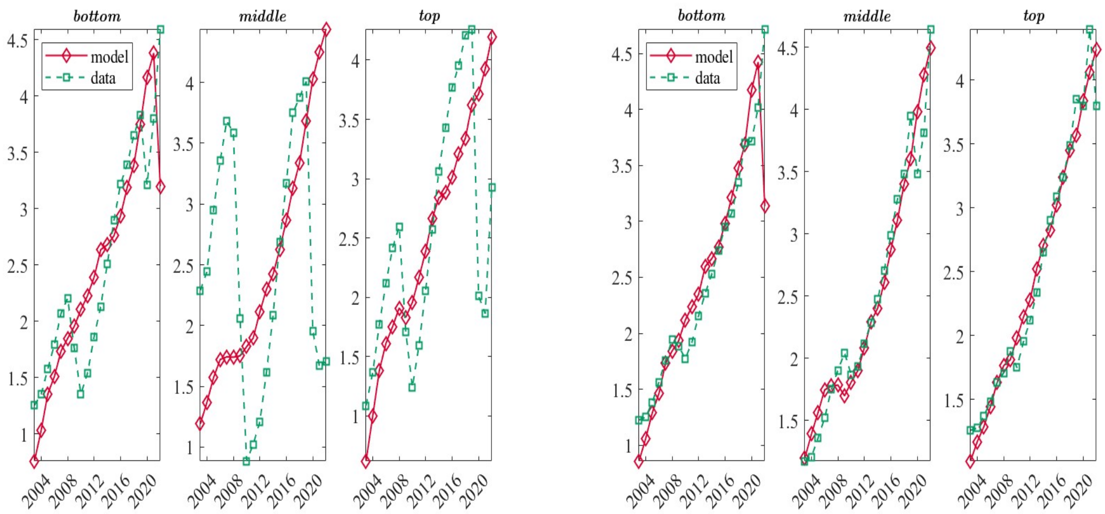
of (or individual) workers, but rather further analysis in this sense should consider the industry where they work. In fact, secondly, changes in the aggregate may hide industry-related heterogeneity, since it is important to consider the industry dimension to account for the impact of business cycle on wage inequality, and especially for industries with an intermediate growth in real wages. Overall, the aim of this section is to better understand the behaviour of employment, and connect it to the evolution of wages through the lens of the theoretical model I have presented. I reach two interesting conclusions that may be worth to further analyse. Business cycle fluctuations are: (i) important to understand the evolution of routine tasks from the perspective of employment only; (ii) substitution among job tasks is driven by the dynamics in their relative wages; and (iii) not trivial to inspect the contribution of middle group of industries on US wage inequality. These considerations may open up new directions in understanding, besides structural trends across industries, the role of business cycle in shaping US wage inequality.

A final comment is devoted at the analysis of the economy-wide employment pattern. The nominal log*-wage dynamics (captured by the model-implied employment) is able to replicate the increasing pattern of aggregate employment in the data bu not cyclical fluctuations, as it is clear in Panel E.4. From my point of view, this implies that there is a limited connection between the two, and that the cyclical component observed in the middle group is pivotal for a better comprehension of the drop in aggregate employment in periods of recession.*[II]

[II] In other words, when considering aggregate employment dynamics not in terms of *absolute* wages, but

Thus, the paper also informs novel sources on the perception of the underlying effects of business cycle on labour income inequality. Considerations should include differences among industries due to the uneven effect on both employment and relative wages at industry level, with larger impact on industries in which wages experienced limited growth. Further analysis on this line are worth to get explored.

rather in terms of *relative* wages − as in the model I present in Section 2, where the labour supply of task-a in industry-s is modelled to be entirely driven by its wage compared to the associated wage level of the economy −, it appears that relative wages play a role only when considering the increasing trend.



(A) EMPLOYMENT, ROUTINES

(B) EMPLOYMENT, NON-ROUTINES

FIGURE E.3: EMPLOYMENT, BY TASKS AND INDUSTRIES

Note: these figures compare the dynamics of the nominal series in the model (solid-red) and in the data (dashed-green). Model-implied employment is defined as in eq. (6), thus measuring employed workforce in terms of industry relative nominal wage. Panel (a) shows movements in industry group specific employment for routine workers, while Panel (b) plots the associated movements for non routine workers. Series are scaled to be in the same range for graphical comparison.

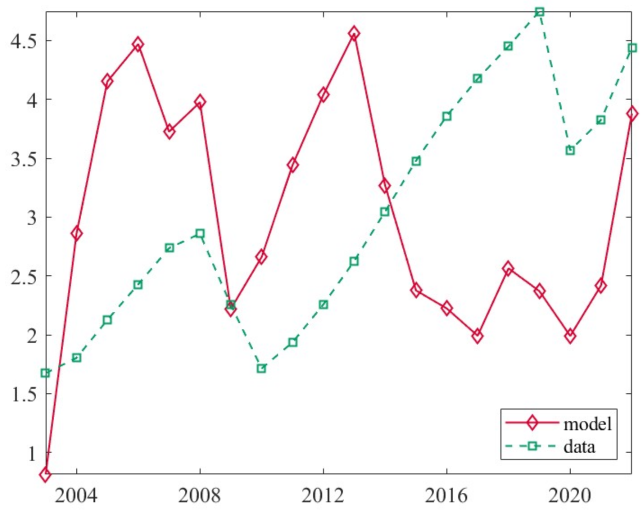
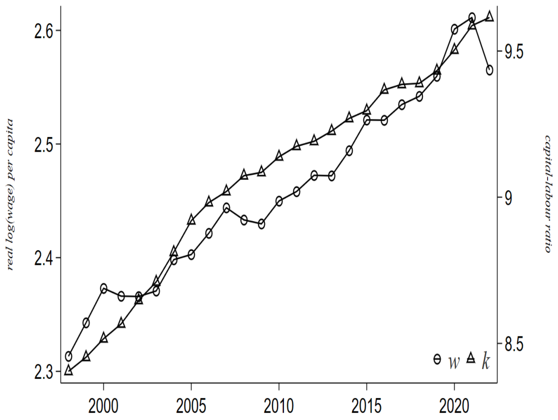


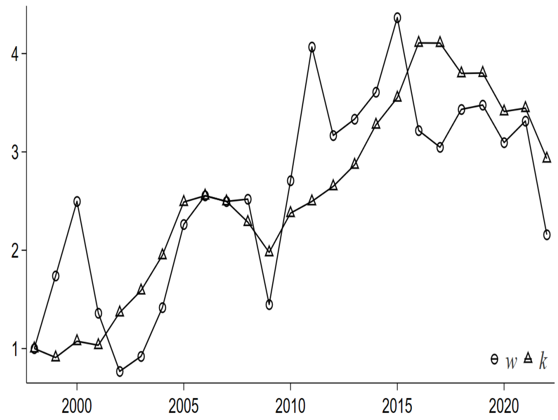
FIGURE E.4: AGGREGATE EMPLOYMENT

Note: this figure plots the evolution of aggregate employment in the economy as measured in the model (solid-red) and in the data (dashed-green) in nominal terms. Series are scaled to be in the same range for graphical comparison.

F. Facts at 2-digit US 2017 NAICS level



(A) Levels



(B) Standard deviations

Figure F.1: Capital and wage series

Note: this figure depicts the evolution of capital and real wages, all taken in per capita *log*-terms, across industries. Panel (a) plots the evolution of series in levels, while Panel (b) plots the associated dispersion measured in standard deviation; series are standardized and indexed to 1 in 1998, so that both y-axis indexes the respective measure given the initial value at unity. Plots are referred to 2-digit US 2017 NAICS industries. *Source*: BEA and own calculations.

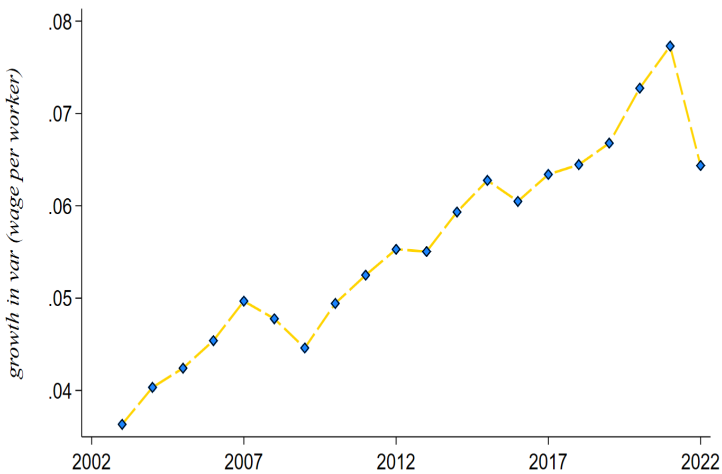
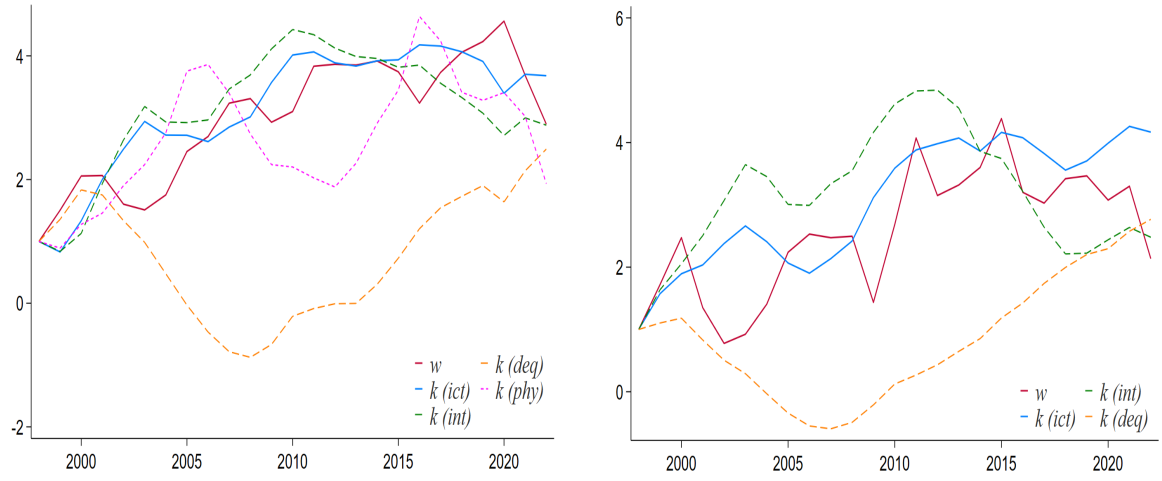


Figure F.2: Between-industry wage variance growth

Note: this figure plots the evolution of between-industry variance growth as defined in eq. (2). Plot is referred to 2-digit US 2017 NAICS industries. *Source*: BEA and own calculations.



(A) INTERQUARTILE RANGE, 90^{th}-10^{th} (B) *log*-VARIANCE

FIGURE F.3: CROSS-INDUSTRIES DISPERSIONS

Note: this figure depicts dispersion across industries of average real *log*-wage, physical, ICT, intangible capital types and digital equipment per capita. Solid red and blue lines are related to wages and ICT capital, while dashed green, orange and purple lines are intangible capital, digital structures, and physical capital, respectively, all taken in per capita *log*-terms. Panel (a) plots the yearly difference between top and bottom 10% of each component, while Panel (b) plots the associated *log*-variance. Series are standardized and indexed to 1 in 1998, so that both y-axis indexes the respective measure given the initial value at unity. Plots are referred to 2-digit US 2017 NAICS industries. *Source*: BEA and own calculations.

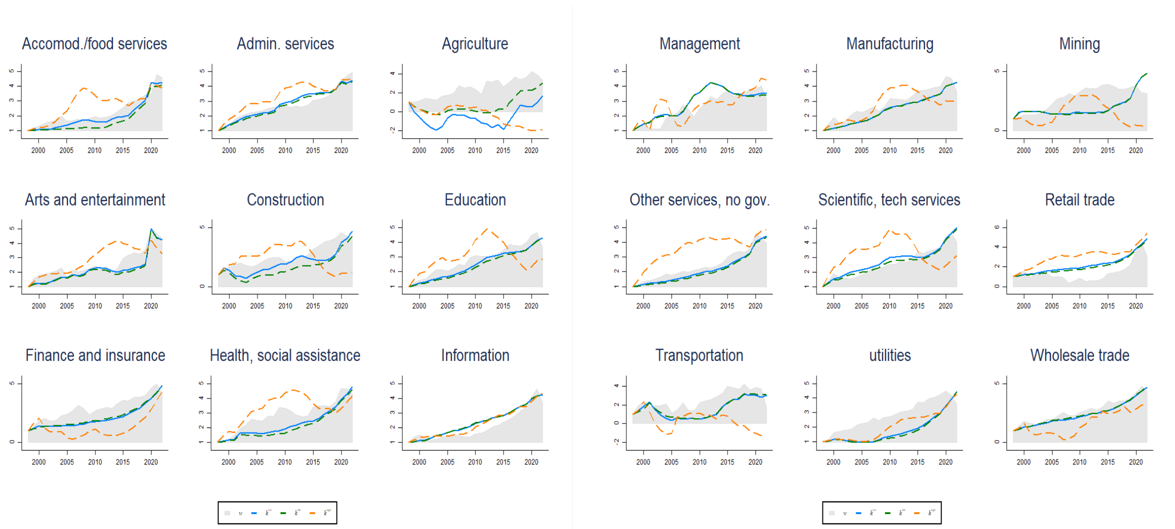


FIGURE F.4: CAPITAL-LABOUR RATIOS AND REAL WAGES

Note: these figures compare the dynamics of real wages (grey-area), ICT capital (solid-blue), intangible capital (dashed-green) and digital structures (dashed-orange), all in per capita terms. Plots are referred to 2-digit US 2017 NAICS industries; *Real estate and rental sector* graph not reported. *Source*: BLS and own calculations.

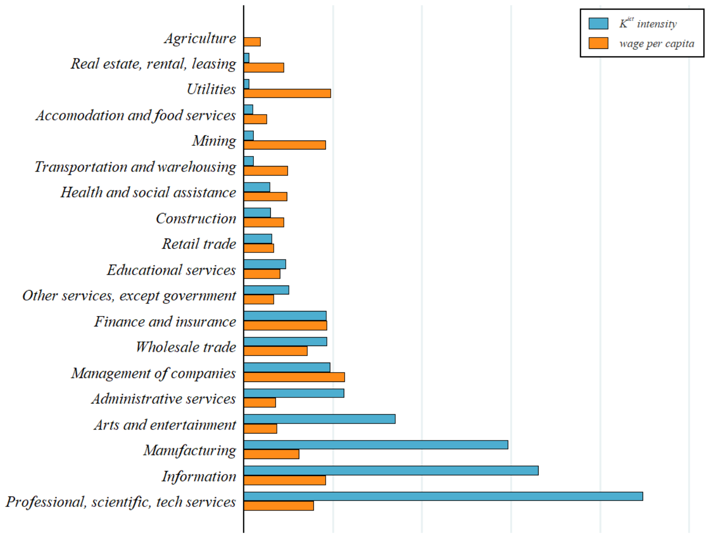


FIGURE F.5: INTANGIBLE INTENSITY AND REAL WAGES

Note: This figure compares the average real wage with the intangible intensity, defined as $INTint_{s,t} = \frac{INTstock_{s,t}}{TotCap_{s,t}}$, of each industry-$s$ over the period 1998-2022. Plot is referred to 2-digit US 2017 NAICS industries. *Source*: BEA and own calculations.

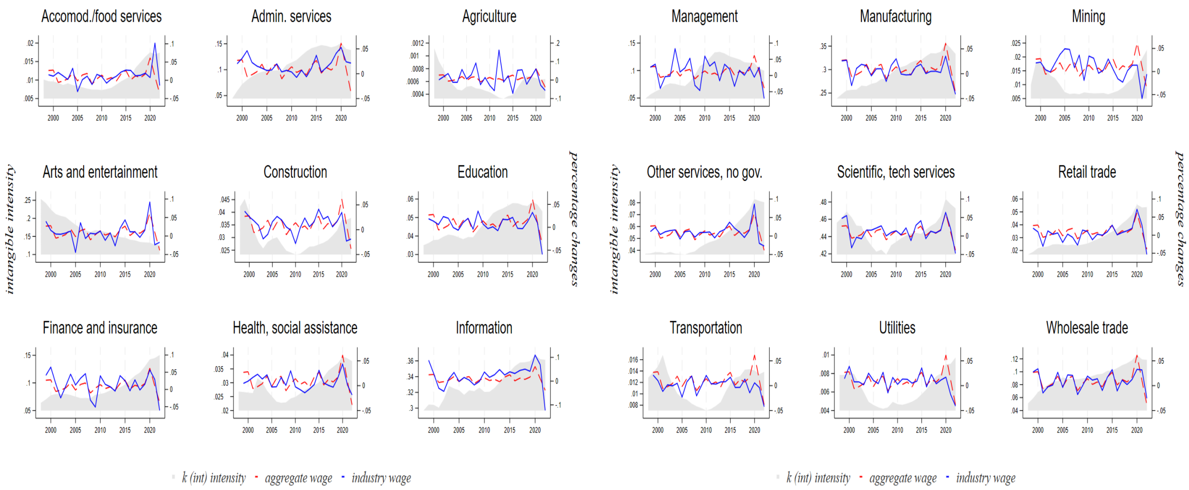
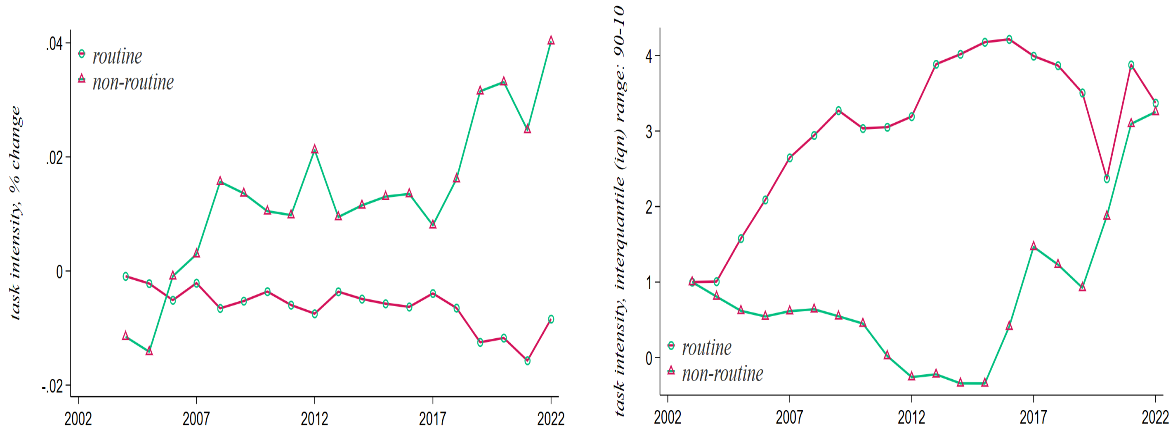


FIGURE F.6: WAGES AND INTANGIBLE INTENSITY

Note: these figures compare the dynamics of intangible intensity (grey-area), and both industry (solid-blue) and aggregate (dashed-red) real per capita log-wage. Plots are referred to 2-digit US 2017 NAICS industries; *Real estate and rental sector* graph not reported. *Source*: BLS and own calculations.



(A) CHANGE IN AGGREGATE TASK INTENSITY

(B) INTERQUARTILE RANGE, 90^{th}-10^{th}

FIGURE F.7: TASK INTENSITY

Note: these figures plot the evolution of task intensity (namely the share of each task in the total employment) of both routine (red) and non-routine (green) workers. Panel (a) depicts the year-by-year percentage change in both series, while Panel (b) plots the yearly difference between top and bottom 10% of each component. Series are standardized and indexed to 1 in 1998, so that both y-axis indexes the respective measure given the initial value at unity. Plots are referred to 2-digit US 2017 NAICS industries. *Source*: BLS and own calculations.

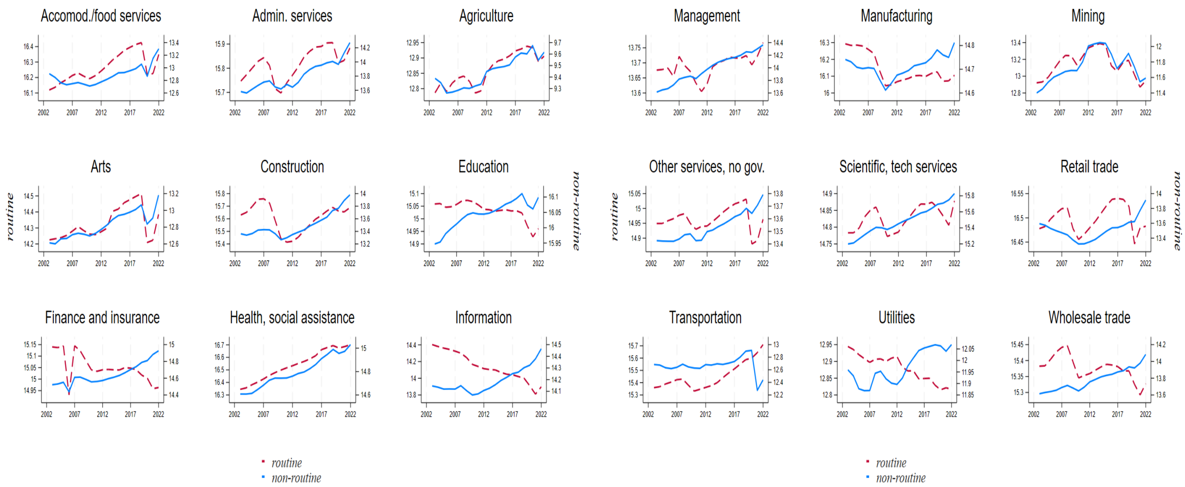
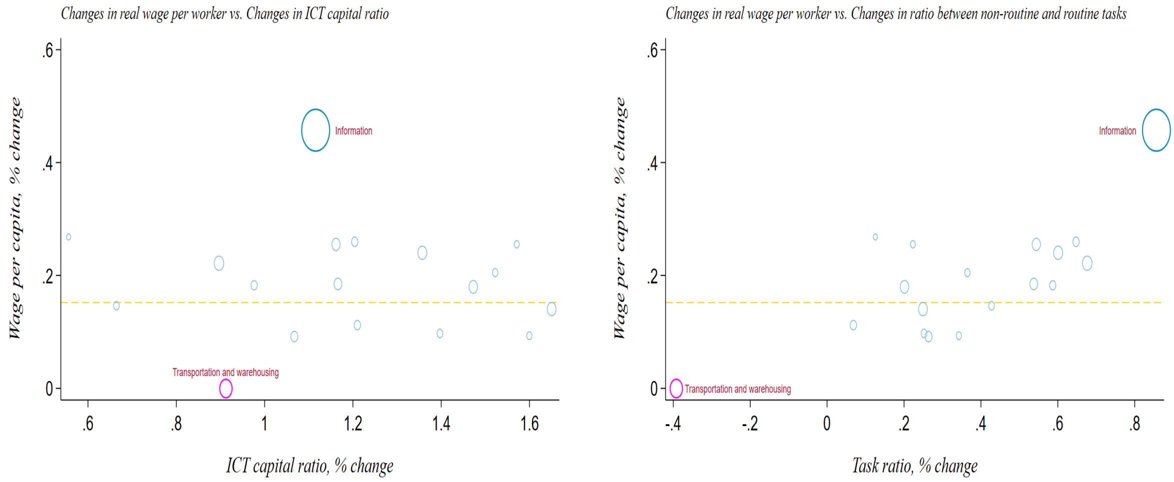


FIGURE F.8: EMPLOYMENT, BY TASKS AND INDUSTRIES

Note: these figures compare the dynamics of the *intensity* of routine (dashed-red) and non-routine (solid-blue) job tasks. Plots are referred to 2-digit US 2017 NAICS industries; *Real estate and rental sector* graph not reported. *Source*: BLS and own calculations.

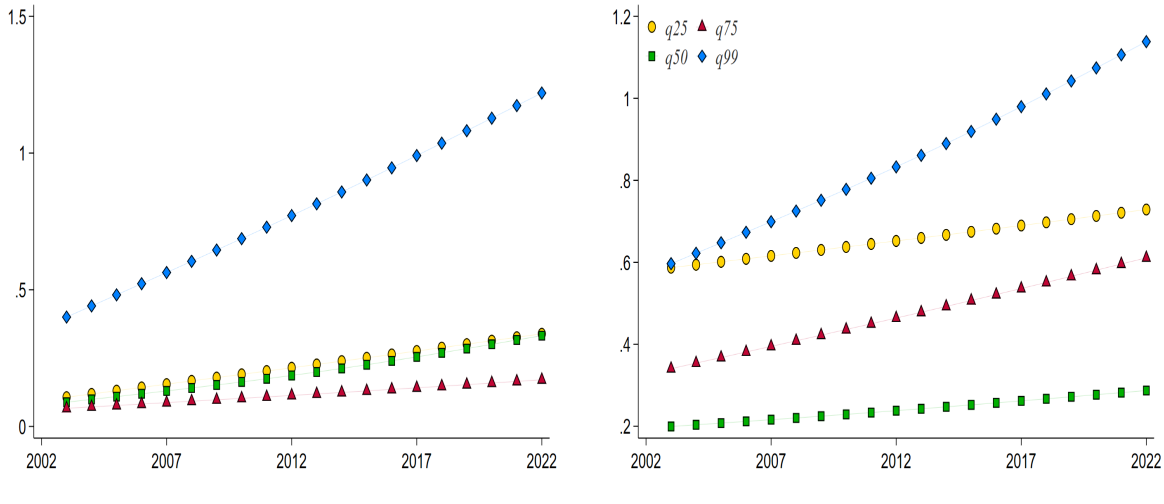


(A) Real wages vs. ICT capital ratio

(B) Real wages vs. task ratio

Figure F.9: Industry Correlations

Note: each subplot of this figure represents the correlation of overall percentage change in both industry-specific real *log*-wage per capita and ICT capital ratio (ICT over non-ICT capital, in Panel (a)) and task ratio (non-routine over routine workers, Panel (b)). The horizontal dashed line in gold identifies the mean value of all industries' percentage change in real *log*-wage per capita. To account for growth in non-ICT capital, the ICT ratio takes constant the initial level of physical capital. Each circle is referred to a specific industry, and I report the label only for more and less virtuous (top and bottom 10%) industries; circles' size captures different group of industries, each expressing the group distribution in terms of overall percentage change in their real *log*-wage. Plots are referred to 2-digit US 2017 NAICS industries over the period 2003-2022. *Source*: BEA, BLS and own calculations.



(A) ICT capital ratio

(B) Task ratio

Figure F.10: Changes by percentiles

Note: each subplot draws the HP-filtered trend in ICT capital ratio (ICT capital stock in physical capital quantity), and in task ratio (fraction of non-routine workers of routine ones), respectively. Series are divided according the growth in group-specific industry wage (*i.e.*, total $\Delta_{\%}$ in industry wage per worker). Plots are referred to 2-digit US 2017 NAICS industries over the period 2003-2022. *Source*: BEA, BLS and own calculations.

References in appendix

Arvai, K. and K. Mann, "Consumption inequality in the digital age", *Banque de France Working Paper Series no. 890* (2022). 53.

Böhm, M. J., D. Metzger, and P. Strömberg, ""Since you're so rich, you must be really smart": talent, rent sharing, and the finance wage premium", *Review of Economic Studies*, vol. 90, no. 5 (2022), pp. 2215-2260. 86.

Eden, M. and P. Gaggl, "On the welfare implications of automation", *Review of Economic Dynamics*, vol. 19 (2018), pp. 15-43. 53.

Freund, L., "Superstar teams: the micro origins and macro implications of coworker complementarities", *Job Market Paper* (2024). 85.

Heathcote, J., F. Perri, and G. L. Violante, "The rise of US earnings inequality: does the cycle drive the trend?", *Review of Economic Dynamics*, vol. 37, no. 1 (2020), pp. S181-S204. 114.

Karabarbounis, L. and B. Neiman, "The global decline of the labor share", *Quarterly Journal of Economics*, vol. 29, no. 1 (2014), pp. 61-103. 64, 73.

Kleinmann, B., "Wage inequality and the spatial expansion of firms", *Job Market Paper* (2023). 60.

Koh, D., R. Santaeulàlia-Llopis, and Y. Zheng, "Labor share decline and Intellectual Property Products capital", *Econometrica*, vol. 88, no. 6 (2020), pp. 2609-2628. 53.

Mc Fadden, D., "A Method of Simulated Moments for estimation of discrete response models without numerical integration", *Econometrica*, vol. 57, no. 5 (1989), pp. 995-1026. 75, 83, 84, 107-109.