Does Digitalization Widen Labor Income Inequality?*

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Preliminary - Comments Welcome

Abstract

Many studies have suggested a positive and monotonic relationship between technological progress and wage income inequality since 1980s for industrialized economies. We examine this topic in the context of the Chinese economy where new generation technologies like automation, AI and digitalization have witnessed world's most rapid growth in the last decade. Surprisingly, we find an inverted U-Shaped relationship - a "Digital Kuznets Curve", using a panel dataset constructed in line with the newly published "2021 Categorization of Core Industries of Digital Economy". We then set out a task-based growth model with heterogenous human capital and occupational choice, and show that this hump-shaped relationship can emerge either by introducing an erosion effect of digitalization on worker ability that increasingly countervails the skill-biasing effect, or by directly adding a dynamic learning cost for human capital accumulation due to the externality of digitalization. Our study contributes to the understanding of the nature of digitalization in re-shaping labor market structure.

Keywords: digitalization, income inequality, human capital, digital externality, worker ability, learning cost

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*All views and errors are ours.

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1 Introduction

With the recent waves of new technology development such as artificial intelligence (AI), robotics and big data, the world economy is experiencing an on-going digital transformation. The Chinese economy, despite being a follower of digital technologies and an emerging market, has achieved prominent progress in digitalization in the last decade in terms of digital transformation, automation and even robots production (see, e.g., Cheng *et al.* 2019). The Chinese government has also provided continuous supportive policies for digitalization[1]. Whilst there has been growing academic research on digital economy for industrialized countries, studies on the Chinese digital economy have been fairly scant. This paper fills this gap by looking at one, probably the most debated, research area of the labor market. Specifically, we study the impacts of digitalization on labor income inequality and provide both empirical evidence and theoretical explanations.

One obstacle for economic research on digital economy lies in the lack of reliable and rich data. To overcome this difficulty, we constructed a panel dataset of China's digitalization with both provincial and industrial dimensions based on the "2021 Categorization of Core Industries of Digital Economy (CCIDE 2021[2], thereafter)" published by the National Bureau of Statistics of China (NBSC) in 2021. It is the first official national accounting of digital economy of China and is mostly compatible with NBSC's existing accounting system. This dataset is valuable in two aspects. First, it represents a comprehensive dataset that covers a wide range of economic activities associated with digital technology. That is, it covers not only digital technologies such as ICT, automation, AI, big data, blockchain and cloud computing, but also "digitalization" as applications of digital technologies. Second, it is a provincial panel dataset that contains rich information about the digital economy at industry level. It can also capture general equilibrium effects and interactions among sectors. This is a clear advantage over few existing firm-level data (See, e.g., Cheng *et al.* 2019 which utilizes CEES survey data) or data extracted from a particular sub-market (e.g., implied data of digital activities from listed companies in Shanghai Stock Market). Figure 1 shows the constructed data of the digital economy of China at aggregate level according to CCIDE 2021.

[1]Examples of such policies include the Robotics Industry Development Plan (2016–2020) by Ministry of Industry and Information Technology (MIIT), "Made in China 2025" program and the fourteenth "5-Year Plan of Digital Economy Development" by the State Council.

[2]The CCIDE 2021 categorization has used the categorization of U.S. Bureau of Economic Analysis (BEA) and OECD for references.

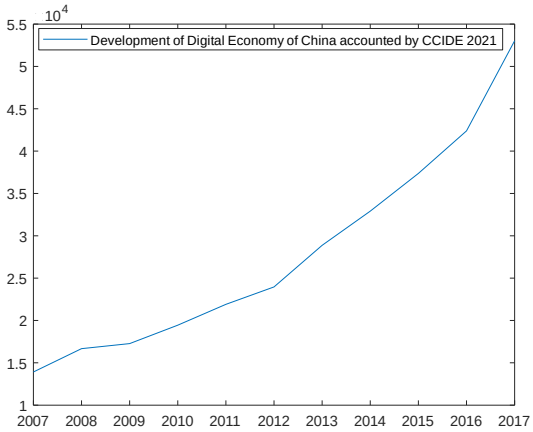


Figure 1: China's Digital Economy: 2007-2017 (100 million RMB)

Much attentions have been paid to the labor market consequences of digitalization, with a focus on jobs and wages. One of the central themes is whether digitalization has widened wage incmoe inequality. This topic has been well studied in developed countries and has reached relatively large consensus that new technologies enlarges wage income gap between groups of workers since 1980s (see, e.g., Goldin and Katz (2009), Acemoglu and Autor (2011), Piketty (2014), Acemoglu Restrepo (2022))[3]. Using our constructed panel dataset, we empirically test this relationship in the Chinese digital economy context. In particular, we employ panel data regressions with two-way fixed effects and instrumental variables to quantify the impacts of digitalization measured by the value-added of digital economy on labor income inequality measured by average wage income across industries for all the counties (See Figure 2) for the time period 2007-2019. In addition, to help understand the relationship, we also conducted mediating effect test to understand the transmission mechanism of digitalization. We constructed a learning cost mediator which is measured by the principle components of telecommunication turnover, internet access and mobile phone users. This design of mediator stems from the hypothesis that digitalization may have nonlinear impacts on learning costs of workers due to the externality of digitalization.

[3]Influences of new technologies on other aspects of labor market, such as labor share and capital income are much more controversial. For example, while replacements of labor by new technologies are confirmed in several studies (e.g., Acemoglu and Restrepo 2020), some positive effects of new technologies remain valid (see, e.g., Acemoglu and Restrepo 2020, and Hemous and Olsen 2022).

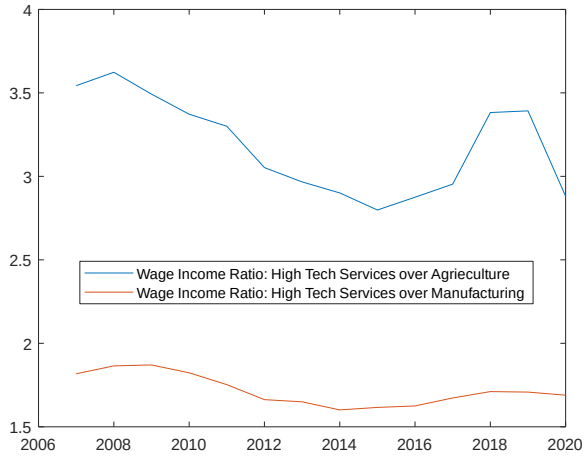


Figure 2: China's labor income inequalities

The empirical results show that, first, there exists a Kuznets curve in Chinese digital economy which characterizes an inverted U-shaped relationship between digitalization and labor income inequality (see Figure 3 for an intuitive illustration when variables are aggregated and averaged). This is in stark contrast with most of the empirical evidence of a monotonic positive relationship found in western countries. In other words, digitalization first increases wage income gap but then there are some countervailing forces that take effect along further digitalization. After digitalization passes the reflection point, countervailing forces dominate, leading to a downward impact on labor income inequality. The extent of the two opposite forces for inequality differs for different entities in the sample due to different reflection points implied for them. Second, the mediation test shows that the learning cost measure is also hump-shaped to digitalization, constituting one possible explanation for the inverted U-shaped relationship between digitalization and wage income inequality. The advances in data-related new technologies impose higher learning costs for workers in society in the beginning but when those technologies further spread out, the learning costs falls.

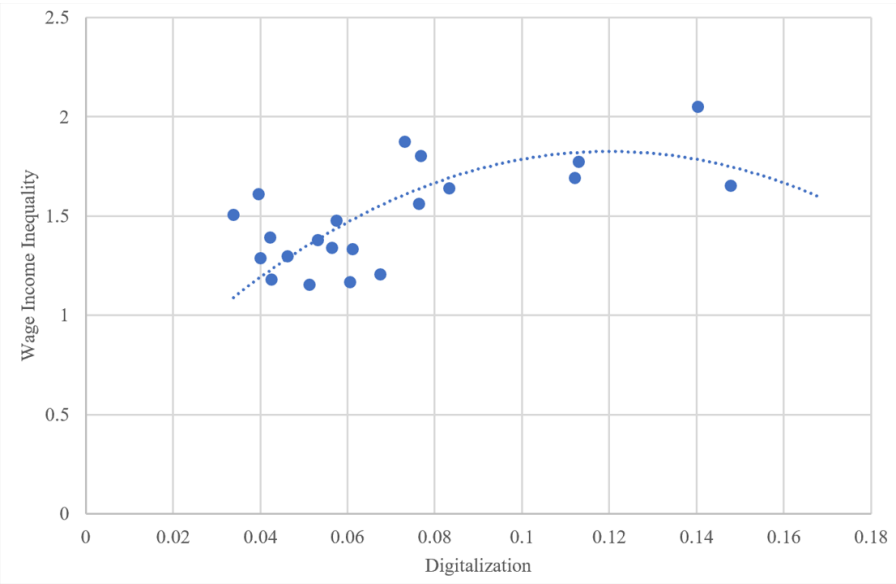


Figure 3: China's digitalization and wage income inequality - The inverted U-shape

There are several reasons for understanding this result. One is that workers are always lagged behind by new technologies. Those data-related technologies are particularly hard to follow when the infrastructure adhered to them are unavailable or below the scale of economy in the early stage. Catching up with those new technologies requiring paying a large amount of education costs desired by tutors who have high opportunity costs of earning information services payrolls. However, when more new technologies emerge and infrastructures are more complete, workers can master the new technologies better and more importantly, through enjoying a more integrated infrastructure and thus lower learning costs. For example, at the later stage of data technology development, workers can make use of online platforms to self-learn e-commerce, online live videoing, take-away riders, designated driving, etc. Those make workers more complementary with new technologies and more likely to transform them toward more data technology industries. Figure 4 depicts some evidence of this conjecture in that throughout the sample period, the number of workers in agriculture falls while the same in high-tech service sector surges. Workers in manufacturing industry shows a hump-shaped process.

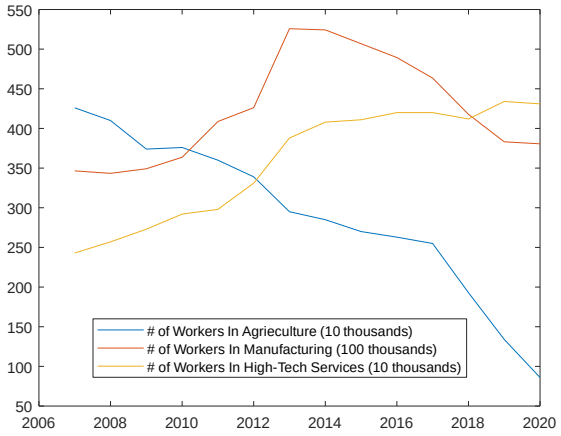


Figure 4: Number of Workers across main Industries in China

To understand the mechanism underlying the digital Kuznets curve described above, we set out a task-based growth model with heterogenous human capital, digitalization technology and nonlinear learning costs of workers. In this model, digitalization works in a similar way with automation and its effects on capital and labor depends on the elasticity of substitution between the two factors (See, e.g., Aghion *et al.* (2017)). We consider the case that digitalization is capital depleting in the long-run and employ a capital-augmenting technology to achieve a balanced growth path (See, e.g., Grossman *et al.* (2017)). We take account of the empirical evidence and model the labor market structure by explicitly discriminating high- and low-skill workers with high and low human capital, mapping those work in high-tech service and manufacturing and agriculture sectors respectively. Then workers with endowment of abilities will solve a occupational choice problem which endogenously determines the quantity of high- and low-skilled workers. Digitalization is skill-biased and higher ability helps accumulate human capital faster as in Galor and Moav (2000). This would result in a monotonic postive relationship between digitalization and wage income inequality. We then depart from this and propose two novel features that dynamically offset this monotonic relation. One is that we introduce a quadratic learning cost to workers who intend to become high-skilled workers. This quadratic form echoes the quadratic term used in the main empirical model, and is commonly used in many adjustment cost functions in finance literature. In notion, we use this form to capture an important yet largely neglected property of digitalization that it can have nonlinear impact on learning ability of all workers due to its positive externality. While it imposes new learning tasks for untrained workers in the beginning, it reduces learning costs of all workers after the ecological system of digital economy becomes more complete. For example, digital platforms provide easier or even free access to new knowledge over

time. This positive externality is a unique feature of digital technology over traditional technologies. The second extension of the model is that we make the distribution of worker ability endogenous. We allow it to positively relate to common technology and negatively depend upon digitalization (analogous to Acemoglu and Restrepo (2018) which uses a evolution rule for technology in the presence of automation). The idea comes from the facts that digital technologies replace not only tasks of unskilled workers but also those of skilled workers. This is more so as digital technologies deepens, a fact increasingly recognized by recent work (see e.g., Brynjolfsson et. al. (2023)). As we show later, this can also make the impact of digitalization on wage income gap nonlinear.

We formulate several propositions to illustrate how these two new features of our model contribute to a successful explanation of the "digital Kuznets curve". In particular, we show that the impact of increases in digitalization on between-group wage inequality is nonlinear (inverted U-shaped) if either one of the assumptions is relaxed: i.e., i) when worker ability region shrinks (linearly) after digitalization; Or ii) there is quadratic learning cost which makes skill and unskilled jobs imperfect substitutes. In addition, Digitalization increases within group inequality of both workers when the distribution of worker ability is fixed, and does not depend on the existence of learning cost. In contrast, digitalization increases within group inequality of unskilled workers but reduces group inequality of skilled workers when the distribution of worker ability is endogenous. We also verify these theoretical predictions with numerical simulations.

The mediating effect of learning cost and the endogenous worker ability distribution channel turn out to be the key to understand the transmission of digitalization on labor income inequality. They are largely ignored in most research on technology-inequality in developed countries. This is not surprising given that empirical studies in the context of developed countries only found monotonic relationship. One exception is the experience of labor market of the US in the 1970s where between-group wage premium fell along with increases within-group wage gaps as a result of increases of labor supply caused by exogenous increases in college graduates. Our study then indicates that the Chinese digital economy in last decade may have experienced the same increase in labor supply as in 1970s for US, but it also has important difference in that it is not driven by increases in college students but a result of hump-shaped learning costs and erosion effect on labor ability driven by digitalization.

This paper contributes to the literature in three folds. First, it provides the first piece of empirical evidence on the nonlinear relationship between new technology and wage income inequality in the context of Chinese economy who is experiencing the most rapid digitalization in the world. The data we use is newly constructed in line with CCIDE

published in 2021 and is consistent with national accounting of NBSC. Second, we propose two novel mechanisms in shaping the hump-shaped relationship. One is the learning cost of workers in face of digitalization explained above. Learning cost affects wage income inequality indirectly through transmitting nonlinearity to the threshold of skilled labor, thus acting as a mediator. The other mechanism is the worker ability distribution channel which nests the positive effect of common technology and the negative effect of digitalization on worker ability. In particular, the erosion effect of digitalization shifts the distribution of worker ability to the left and thus becomes a countervailing force that offsets the positive monotonic impact of digitalization on inequality. Both mechanisms provide new insights to the nature and transmission channels of digitalization to macroeconomy. Last but not least, our study points to the importance of the supply behavior of labor whereas most existing literature only focus on labor demand. We thus deepen the understanding of the impacts of new technology on changes in labor structure in terms of human capital accumulation and labor choice. The findings of this study are helpful for understanding the nature of the impact of digitalization on labor market and have important implications for government policy.

The paper is organized as follows. Section 2 provides a literature review on the relationship between technology and inequality. The empirical examination of this relationship in the context of the Chinese economy is conducted in Section 3. Section 4 sets out a theoretical task-based growth model with heterogenous human capital, worker ability and learning cost. Section 5 conducts numerical simulations. Section 6 concludes.

2 Related Literature

This paper lies generally in the relationship between technology progress and inequality. The famous Kuznets Curve (Kuznets, 1955) depicts an inverted U-shaped relationship between economic growth and inequality. Since technology is the main driving force of economic growth, the Kuznets Curve implies also a hump-shaped relationship between technology and income inequality. However, this inverted U-Shape was soon overturned by researchers in 1990s due to the observation that Kuznets Curve only existed between 1915-1940s, after which the curve dropped substantially, remaining flat during 1960s-1970s, and sloped upward sharply since 1980s (Goldin and Katz 2009, Picketty 2014, Kasa and Lei (2018)). Therefore, in the long run, the relationship between technology and inequality looks more like an U-shape. Researchers attribute the change in the shape of Kuznets curve to several factors, such as World War II (e.g., Milanovic, 2016), the rising of educated workers and higher human capital after 1940s (e.g., Goldin and Katz 2009), and

Skill-biased Technical Change (SBTC) after 1980s (e.g., Katz and Murphy 1992, Acemoglu 1998). Since 1980s, a bunch of 'new technologies' has broken through and diffused across the economy. Nonetheless, the technology-inequality relationship has remained increasing. Recent research paradigm on this issue largely follow the SBTC approach but taking new features of the new technologies into account. For example, technology may be still skill-biased in that human capital is more complementary with it (Galor and Moav 2000). For another, new technology can endogenously choose to augment capital or labor depending on its nature, following the Directed Technical Change (DCT) literature (Acemoglu 1998). Moreover, high-skilled labor may be complements with robots (Hemous and Olsen 2022). Among these new research directions, task-based model has gained popularity due to its flexibility and to that it can generate replacement effect that is absent in DCT models. Summarizing this strand of literature, we find little evidence of Kuznets curve after 1980s in developed countries. Up to our best knowledge, there are only two work that delivers inverted U-shape in developed countries[4]. Borghans and Weel (2007) find that computer adoption causes Inverted U-shape of wage inequality when allowing workers decide endogenously whether and when to adopt computer basing on cost-benefit analysis. Their results are consistent with German wage structure during 1980s. Bohm *et al.* (2015) develop a two sector production model with immobile labour supply and directed technical change toward high-skilled human capital. They show that public policies that subsidize higher education costs for high-skilled workers raise inequality (in terms of wage rates, consumption and income) in the short run (3 decades), whereas they are beneficial for low-skilled workers in the long run. But their work is purely theoretical without empirical evidence. Our contribution to this literature is that we provide the first evidence for a digital Kuznets curve after 1980s and explain it using a theoretical model.

Our study also sheds light on the recent debate on labor market consequences of digital technologies. In the early stage of information revolution, Kuhn and Mansour (2014) find empirical evidence that internet usage reduces job search costs. In the recent automation and aritificial intelligence, Acemoglu and Restrepo (2018, 2020, 2022) study the impacts of adoptions of robots on US labor market using industrial and firm-level data. They find that labor share has fallen and the inequality between workers has enlarged as a result of automation. Those new trends of labor market outcomes are then explained in several task-based growth models which allow for various substitutional and compensational effects of automation. Frey (2020) compare different waves of automation and their different impacts

[4]There are two research work (Acemoglu and Autor (2011) and Prettner and Schaefer (2021)) that generate nonlinear relationship between technology and wage inequality. But they deliver U-shape rather than hump-shape.

on capital and labor. Korinek and Juelfs (2022) critically analyze the displacement effect of AI and automation and propose cases where human labor are still needed in future. Gomes *et al.* (2022) use an unique Sweden dataset which can capture people's exposure to robots, wealth rankings and demographics. They find quite large effects of automation on wealth distribution through a portfolio adjustment mechanism. We extend this literature by providing a new evidence in the context of the Chinese economy where continuous digitalization has been on going. Our theoretical framework, particularly the way we model digitalization in the production function share many similarities with that of modelling automation, but we allow for its direct and interactive effects on labor market.

In the aforementioned literature, the emphasis has been put on changes in labor demand. This is straight forward as technologies should affect labor directly or indirectly. However, labor supply also plays important roles in occupational choices and labor mobility. Examples of labor supply analysis include Katz and Murphy (1992), Acemoglu (1998), Aghion (2002), Grossman *et al.* (2017) and Hemous and Olsen (2022). Occupational choice is explicitly modelled in Galor and Moav (2000), Kambourov and Manovskii (2008, 2009), Dvorkin and Naranjo (2019). Costs of labor mobility has been discussed in Cortes and Gallipoli (2018). For developing countries, Du *et al.* (2014) and Ge and Yang (2014) document the continued influx of rural migrant workers to the industrial sector and their contribution to the productivity of labor-intensive industries. Therefore, our contribution to labor market literature by examining how digitalization affects workers' labor supply behavior.

The idea that digitalization affects human capital of workers is also directly related to the literature of the economics of data, especially in the externalities of data (due to nonrivalry)[5] and its consequences on growth, welfare and inequality. Jones et. al. (2020) examines the nonrivalry property of data and the positive externality it generates for society, and analyze its tradeoff with privacy in different ownership settings and government regulation schemes. Their finding is that authorize data ownership to consumers rather than firms delivers much higher welfare close to optimum as firms have less incentives to sell data to others. Cong et. al. (2021)[6] feed consumer generated data into production of goods to allow for semi-endogenous growth and find that on the balanced growth path a decentralized economy incurs welfare loss due to underemployment and overuse of data

[5]Ghosh et. al. (2021) identifies the impact of digitalization on financial market. They demonstrate both theoretically and empirically that FinTech lenders can achieve higher efficiency of screening borrowers when the latter use cashless payments and generate transferrable and verifiable information.

[6]Cong et. al. (2022) extend to vertical nonrivalry of data and a fully endogenous growth model where consumer-generated data can be shared with both production and innovation sectors. The innovation sector dominates production sector in the matter of long-run growth due to its advantage that, beside its dynamic nonrivalry, it "desensitizes" raw data into knowledge which avoids consumers' privacy concerns.

compared with the social optimum. Their model implies that *income gap* in the digital economy could be enlarged especially during the early stage of the balance growth path because economies starting from low initial growth generate low volume of data. In contrast, Ichihashi (2021), Acemoglu et. al. (2022) and Bergemann et. al. (2022) identify negative externalities, where the sharing of data of one consumer might reveal other consumers data, causing inefficient over-provision of data. Liu et. al. (2023) uncovers a new negative externality due to behavioral biases such as the existence of consumers with self-control problems to temptation goods. This offsets nonrivalry property of data and calls for consumer privacy protection. In addition, due to the existence of weak-willed consumers, digitalization raises total efficiency but at a price of widening welfare gap between strong- and weak-will consumers, which they named a *'algorithmic inequality'* problem. Farboodi and Veldkamp (2022) proposes a dynamic equilibrium model of the data economy taking data as an input of production and as a state variable with depreciation. They show that the long-run dynamics of data resembles decreasing returns to scale but it displays increasing returns to scale in the short-run. In particular, *a poverty trap* presents in the short-run between and large and small firms due the former taking advantage of increasing returns of data they generate during growth. In a related work, Farboodi et. al. (2022) develops a cross-sectional measure of data and documents a new fact of *data divergence* that, as large firms get larger, they attract much more data than other firms. Our work shares similar idea of externality of data with the above researchers but differs in that we also notice the possibility that digital technology is also nonrivalry among workers and can change their ability distribution and occupational choice in a dynamic way. In addition, although some of the above papers discussed the inequality implications of digitalization, none of them focuses on labor market outcomes. In this sense, our work is closely related to a recent work by Brynjolfsson et. al. (2023) which demonstrates that newly emerged generative AI transmits the tacit knowledge of more skilled workers to low skilled workers and helps newer workers learn things faster. Our empirical evidence and theoretical analysis in this paper suggest that these dynamic learning effects on workers human capital may have taken effect well before the emergence of Generative AI.

Finally, it is noted that, our finding of an inverted U-shaped relationship between technology and inequality is not the only case in developing countries. Che and Zhang (2017) uses higher education expansion 2003 as a natural experiment to examine its impact on tech adoption and TFP. They also empirically estimated the impact of education expansion on wage premium (using industry consensus data, 1995 and 2004). They show that college expansion cause increases of supply of high-skilled labor which drags down wage premium despite the increased demand for high-skills positions the same time. The whole dynamics

show a humped shape (inverted U-shape): first increasing (1999-2002), then decreasing (2003-2007). Their work however, is subject to two drawbacks: i) it does not provide theoretical explanation of the underlying mechanism; ii) In their paper, education is purely exogenous, not a consequence of endogenous choice.

Ge and Yang (2014) use Chinese urban household survey data and find that capital accumulation, skill-biased technological change, and rural-urban migration to be the major forces behind the evolving wage structure in urban China. Importantly, their model simulation reveals that high school wage premium and college wage premium can show inverted U-Shape 1992-2007 (peak in 2001). They argue that this is consistent with the dramatic expansion in college enrolment that started in the late 1990s and the subsequent increase in the supply of college-educated workers. Our paper complements their work by examining wage premium across industries in the digital era.

Besides, there are two additional empirical work in support of the existence of Kuznets curve. Messina and Silva (2019) find inverted U-Shape for Latin America wage inequality 1995-2015. They propose education attainment as the main reason for this nonlinearity as it reduces wages of college and high school graduates, and also of more experienced workers. However, they also find that two thirds of wage inequality decline is due to within group wage inequality, therefore reveals only limited role of labor supply effect emphasized by our paper. Castello-Climent and Domenech (2021) show that human capital inequality (as share of population with no schooling) has inverted U-Shape relationship with labor income inequality (146 countries, 1950-2010), but SBTC could have offset the effect of the fall in human capital inequality over time. We complement this literature by providing a theoretical framework to understand the mechanisms underlining these empirical patterns.

3 Empirical Evidence

3.1 Data

We constructed a panel dataset of China's digitalization with both provincial and industrial dimensions based on the "2021 Categorization of Core Industries of Digital Economy (CCIDE 2021). This Categorization has four major categories: digital products manufacturing, digital product services, digital technology application and data-driven industries. The first two categories focus on the new technologies in production of digital goods and services while the last two focus on digitalization of industries by adopting digital goods and services. As a result, it provides us a much wider measure of "digital technology'.

The data used for constructing digital economy measures comes from three main sources: Firstly, the input-output tables of each province for more than 100 sectors in 2007, 2012

and 2017. The input-output tables for more than 100 sectors have relatively detailed industry divisions and is the basis of statistical accounting for the digital economy, covering 21 provinces. Secondly, the 2008 and 2013 China Economic Census Yearbooks. Combining them with the input-output tables of each province, the value added of the digital economy in each province can be calculated. Thirdly, the statistics at the provincial level, including indicators such as skill premium, GDP per capita, fixed capital stock per capita and urbanization rate, are mainly from provincial and municipal statistical yearbooks and the China Statistical Yearbook.

Table 1: Description of Variables

Variables	Formula of Construction
premium1	Wage income ratio between Science & technology and manufacturing
premium2	Wage income ratio between Science & Technology and Agriculture, Forestry and Fisheries
digit	Logarithm of the Overall Value Added of the digital economy
$digit^2$	The square of digit
prop	Share of overall value added of the digital economy
$prop^2$	The square of prop
perk	Capital stock/Resident population
gdp	Gross production/Resident population
urban	Urban employed population/Total population
cost	Consumer spending/Disposable income
industryad	Tertiary sector output/Secondary sector output
industryra	Tertiary sector output/GDP
social	Social security expenditure/General budget expenditure
edu	Education expenditure/General budget expenditure
fdi	Total investment in foreign-invested enterprises/GDP
imandex	Total imports and exports/GDP
state	Employees in state-owned enterprises/total employment

3.2 Descriptive Statistics

The meanings and descriptive statistics of the variables used in the measurement are described in Table 1 & 2. The explained variable include two measures of skill premium: the ratio of the average wage in science and technology to the average wage in manufacturing: premium1, and the ratio of the average wage in science and technology to the average wage in agriculture, forestry and fisheries: premium2. Premium1 is used as the main measure of skill premium and the other indicator was used as the explanatory variable in the robustness test.

Table 2 Descriptive Statistics of Variables

Variables	Obs	Mean	Std. Dev	Min	Max
premium1	434	2.337	0.793	1.267	6.881
premium2	434	1.482	0.276	0.949	3.12
digit	231	6.677	1.096	3.625	9.432
$digit^2$	231	45.774	14.789	13.139	88.957
prop	231	0.07	0.034	0.026	0.191
$prop^2$	231	0.006	0.006	0.001	0.037
perk	330	17.37	9.433	2.952	56.403
gdp	434	10.566	0.566	8.959	12.009
urban	434	0.554	0.142	0.215	0.896
cost	434	0.736	0.055	0.56	0.905
industryad	434	1.251	0.688	0.527	5.244
industryra	434	0.476	0.093	0.298	0.837
social	434	0.13	0.035	0.055	0.276
edu	434	0.163	0.026	0.099	0.222
fdi	434	0.505	1.837	0.047	37.212
imandex	434	0.289	0.325	0.008	1.587
state	434	0.331	0.135	0.083	0.842

The explanatory variable is the scale of development of the digital economy in each province in China. According to the methodology of the US Bureau of Economic Analysis (BEA), the scale of digital economy at the provincial and municipal levels was statistically accounted for using input-output tables, statistical yearbooks and economic census data in 21 provinces, based on the Catalogue of Core Industries of the Digital Economy (2021) published by the National Bureau of Statistics. The accounting is divided into four sections: digital product manufacturing, digital product services, digital technology applications and data-driven industries, as shown in the Table 2.

In the model, 11 variables were selected as control variables from five perspectives, reflecting five aspects: level of economic development, structural changes in the economy, government behavior, international trade and the marketization process. See Table 1 for details.

Table 3: Sizes of Digital Economy in Selected Provinces and Municipalities in 2017

	Digital Product Manufacturing	Digital Product Services	Digital Technology Application	Data-driven Industries	Share to GDP
Beijing	428.6585	70.95416	3666.653	200.9252	14.61
Tianjin	487.7475	60.5429	520.6288	55.8851	9.03
Zhejiang	1770.319	165.9525	2716.879	182.2212	9.22
Jiangsu	5324.442	211.7899	3012.713	316.8356	10.32
Fujian	1295.28	62.79458	820.7065	76.24486	6.66
Guangdong	8388.932	253.0411	3913.783	205.0231	13.92
Liaoning	478.6626	52.17442	577.1305	48.5994	5.33
Jilin	125.794	91.38116	361.2722	54.60505	5.79
Heilongjiang	105.4805	23.63477	215.2625	19.60313	2.95
Sichuan	1358.679	90.07507	1687.829	59.7422	8.43
Guizhou	169.7666	27.29571	380.6914	44.4132	4.57
Yunnan	171.6392	50.94098	504.3869	67.17601	4.29

3.3 Empirical Model

Combined with the previous theoretical analysis, we first develop a model between the digital economy and the skill premium, with the digital economy taken as logarithmic. The empirical model is as follows.

$$premium_{i,t} = \alpha_0 + \alpha_1 digit_{i,t} + \alpha_2 digit_{i,t}^2 + \alpha_3 X_{i,t} + \alpha_t + \alpha_i + \varepsilon_{i,t} \quad (1)$$

where $premium_{i,t}$ denotes the skill premium, $digit_{i,t}$ denotes the level of digital economy development, and $X_{i,t}$ denotes a set of control variables that affect the skill premium. The subscripts i and t denote province and year respectively; α_i denotes unobservable province fixed effects, with individual fixed effects added to control for province characteristics; α_t denotes time fixed effects, with time fixed effects added to control for year-specific event effects; and $\varepsilon_{i,t}$ is the error term. Meanwhile, we analyze the relationship between the development of the digital economy and the skills premium at the district level, so the standard errors are clustered to the district level. According to model (1), α_1 and α_2 measure the overall impact of the development of the digital economy on the skills premium.

In terms of transmission mechanisms, we need to verify that "the digital economy affects learning ability through an inverted U-shaped curve effect, which in turn affects the skill premium and contributes to the inverted U-shaped relationship between the digital economy and skill premium". We use the "three-step" approach developed by Baron and

Kenny (1986) to test for mediating effects. Therefore, in addition to model 1, the following model is required:

$$growth_{i,t} = \beta_0 + \beta_1 digit_{i,t} + \beta_2 digit_{i,t}^2 + \beta_3 X_{i,t} + \alpha_t + \alpha_i + \varepsilon_{i,t} \tag{2}$$

$$premium_{i,t} = \gamma_0 + \gamma_1 digit_{i,t} + \gamma_2 digit_{i,t}^2 + \gamma_3 growth_{i,t} + \gamma_4 X_{i,t} + \alpha_t + \alpha_i + \varepsilon_{i,t} \tag{3}$$

where $\text{growth}_{i,t}$ denotes the speed of digital technology progress, and will be used as our mediating variable. The four indicators: total telecommunication services per capita, Internet broadband access subscribers, number of mobile phone subscribers and IT service revenue are regressed on the principal components and the principal components are extracted to form a composite index representing the level of development of digital technology. The growth rate of this index is then taken to represent the speed of digital technology progress. Model (2) can test whether the digital economy affects learning ability through an inverted u-shaped curve effect, while model (3) can test whether the speed of progress of digital technology is a fully mediated or partially mediated effect in it.

3.4 Results

3.4.1 Benchmark Model

The benchmark results for the impact of the digital economy on the skills premium are given in Table 4. The empirical results in column (2) show that all other factors being equal, the coefficient of the primary term of the digital economy on the skill premium is 1.181 and the coefficient of the squared term of the digital economy on the skill premium is -0.0772, both passing the significance test. In other words, the digital economy has an "inverted U" shaped effect on the skill premium.

Table 4: Base model regression results

Variable	(1) premium1	(2) premium1	(3) premium2	(4) premium2
digit	0.0534	1.181***	0.763**	2.382***
	(0.53)	(4.69)	(2.18)	(4.47)
digit^2		-0.0772***		-0.111***
		(-5.53)		(-3.35)
Control variables	YES	YES	YES	YES
Year effect	YES	YES	YES	YES
Provincial effects	YES	YES	YES	YES
N	231	231	231	231
adj-R^2	0.5093	0.6101	0.4427	0.4927

t statistics in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.4.2 Robustness

(1) Replacement of explanatory variables By replacing the value added of the digital economy with the share of the digital economy in GDP(prop), the empirical results in columns (1) and (2) of Table 4 show that the share of the digital economy in GDP still shows a significant inverted U-shaped relationship with the skill premium.

(2) Instrumental variables test Although the introduction of year and province as control variables in the previous model can solve the endogeneity problem to a certain extent, it cannot completely avoid the endogeneity problem caused by omitted variables and so on. Based on this, instrumental variables are introduced to further address the endogeneity problem, and a two-stage OLS regression is conducted using the one-period lag of the digital economy as the instrumental variable. The one-period lagged variable, as a traditional instrumental variable, is able to meet the requirements of relevance and exclusivity. Columns (3) and (4) of Table 5 give the regression results for the instrumental variables. Firstly, the results of the under-identification test (Kleibergen-Paap rk LM statistic test) as well as the weak identification test (Cragg-Donald Wald F statistic test) for the instrumental variables prove the validity of the instrumental variables. Secondly, the empirical results suggest that digital economy still shows an inverted U-shaped relationship with the skill premium and is more significant. Columns (5) and (6) of Table 4 replace the skill premium variable and the model is more robust, with no significant change in coefficients or significance, and the inverted U-shape relationship is still significant.

Table 5: Robustness tests

Variable	(1) premium1	(2) premium1	(3) premium1	(4) premium1	(5) premium2	(6) premium2
prop	-2.281	9.632**				
	(-1.23)	(2.41)				
$prop^2$		-63.55***				
		(-2.98)				
digit			0.137	1.363***	0.877***	2.441***
			(1.49)	(5.64)	(3.84)	(5.85)
$digit^2$				-0.088***		-0.112***
				(-6.05)		(-4.34)
Control variables	YES	YES	YES	YES	YES	YES
Year effect	YES	YES	YES	YES	YES	YES
Provincial effects	YES	YES	YES	YES	YES	YES
LM statistic			42.864	44.728	42.864	44.728
			(0.00)	(0.00)	(0.00)	(0.00)
Wald F statistic			656.56	322.176	656.56	322.176
			(16.38)	(7.03)	(16.38)	(7.03)
N	231	231	210	210	210	210
adj-R^2	0.5184	0.5659	0.5216	0.6135	0.4598	0.4990

t statistics in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.4.3 Mediating Effect

The results of the test for the intermediate effect are shown in Table 6. Column (2) shows that the coefficient of impact of the digital economy primary term (digit) on the speed of digital skill progress (growth) is 3.918, and the coefficient of impact of the digital economy squared term ($digit^2$) on the speed of digital skill progress (growth) is -0.296, and both pass the significance test at the 1% level, in other words, the relationship between the digital economy and the rate of digital skill progress shows an inverted U-shaped curve. In column (3), the coefficient of the impact of the speed of digital technological progress on the skill premium is 0.262 and passes the significance test at the 5% level, indicating that the faster the speed of digital technological progress, the stronger the advantage of high-skilled labour, and then the greater the skill premium. Therefore, the mediating effect of the speed of digital technology progress is significant.

Table 6: Mediating effects Test

	(1)	(2)	(3)
Variable	premium1	growth	premium1
digit	1.363***	3.918***	-1.074
	(5.64)	(5.25)	(-2.02)
$digit^2$	-0.088***	-0.296***	0.0863
	(-6.05)	(-5.91)	(2.32)
growth			0.262**
			(3.17)
Control variables	YES	YES	YES
Instrumental variable	YES	YES	YES
Year effect	YES	YES	YES
Provincial effects	YES	YES	YES
N	210	54	54
adj-R^2	0.6135	0.7223	0.7238
Intermediary effects		Significant	

t statistics in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4 Theoretical Model

In this section, we set out a theoretical model to help understand the "digital Kuznets curve" found in the empirical section above. Intuitively, a hump-shaped relationship between digitalization and wage income inequality must come from at least two countervailing forces at work the same time. Some recent growth models in the literature has noticed multiples effects of digital technology, e.g., labor displacement effects versus productivity effects and non-rivalry of data, but none of them examined the specific nonlinearity they may exert. In addition, they focus mainly on the firm side effects of digital technology and how it affects labor demand, but ignored how it may change labor supply of workers. We build a growth model where digitalization creates countervailing forces both in labor demand and labor supply. Specifically, we start from a canonical task-based growth model (see, e.g., Aghion *et al.* 2018) with CES production function where digitalized and un-digitalized tasks are complements so that digitalization is actually capital-depleting and labor-augmenting. This helps the model achieve a unique balanced growth path in the presence of digitalization. On the labor supply side, which is the main focus of our paper, we model labor market as consisting of skilled and un-skilled workers who are endowed with high and low human capital and also different abilities to learn. Although the digital technology is skill-biased and thus would induce monotonic and increasing wage income

gap between the two groups of workers, we introduce two new features to offset it dynamically. One feature is that that workers must pay learning costs if he/she intends to become a skill-worker, thus making the two jobs imperfect substitutes. Critically, due to positive externality and nonrivalry of digital technology, the learning cost function is nonlinear (quadratic). It makes unskilled workers harder to change occupation in the beginning due to increasing learning costs, but then turns to facilitate it when learning costs of all workers are reduced in later stage of digitalization. This is a 'first harm the bottom then benefit all' mechnism. A second feature we extend to this model is to recognize the new feature of digilization where not only tasks of unskilled but also that of skilled workers are replaced by digitalization (recent evidence by Brynjolfsson et. al. (2023)). We model this feature by endogenizing the distribution of worker abilities as a negative function of digitalization, a rationale similar with Acemoglu and Restrepo (2018). This is a "harm all" mechanism[7]. We will show below that both new features matter for occupation choices of workers and can bring about an inverted U-shape relationship between digitalization and wage income inequality.

4.1 Economic Environment

There are representative firms and heterogenous workers, i.e., skilled and unskilled, in the economy. Goods market and factor markets are all perfectly competitive. Workers are endowed with abilities that follow a distribution in the domain between $[A_t - 1, A_t]$. They make occupational choices between skilled and unskilled workers at time t-1. Workers who decide to become skilled ones invest in human capital by paying learning cost. In period t, both skilled and unskilled workers work for firms and receive wage income. In time t+1, both workers retire and spend all of their income for consumption and investment. For simplicity, worker save a constant fraction of net wage income in period t. Firms on the other hand produce intermediate goods with digitalized and undigitalized tasks following Zeira (1998), Aghion *et al.* (2018) and Acemoglu and Restrepo (2018). Perfect competition in factor markets and optimal uses of them lead to aggregate production function of final goods. The structure of model is depicted in the flow chart diagram in Figure 5.

[7]Some recent General AI technologies such as ChatGPT may even have an asymmetric influence on jobs where it replaces more skilled jobs (such as programmers, financial market brokers and analysts, etc.) rather than unskilled jobs (those reply more on physical tasks). Employing such asymmetric change in distribution of worker ability will make the result of our second feature even more significant.

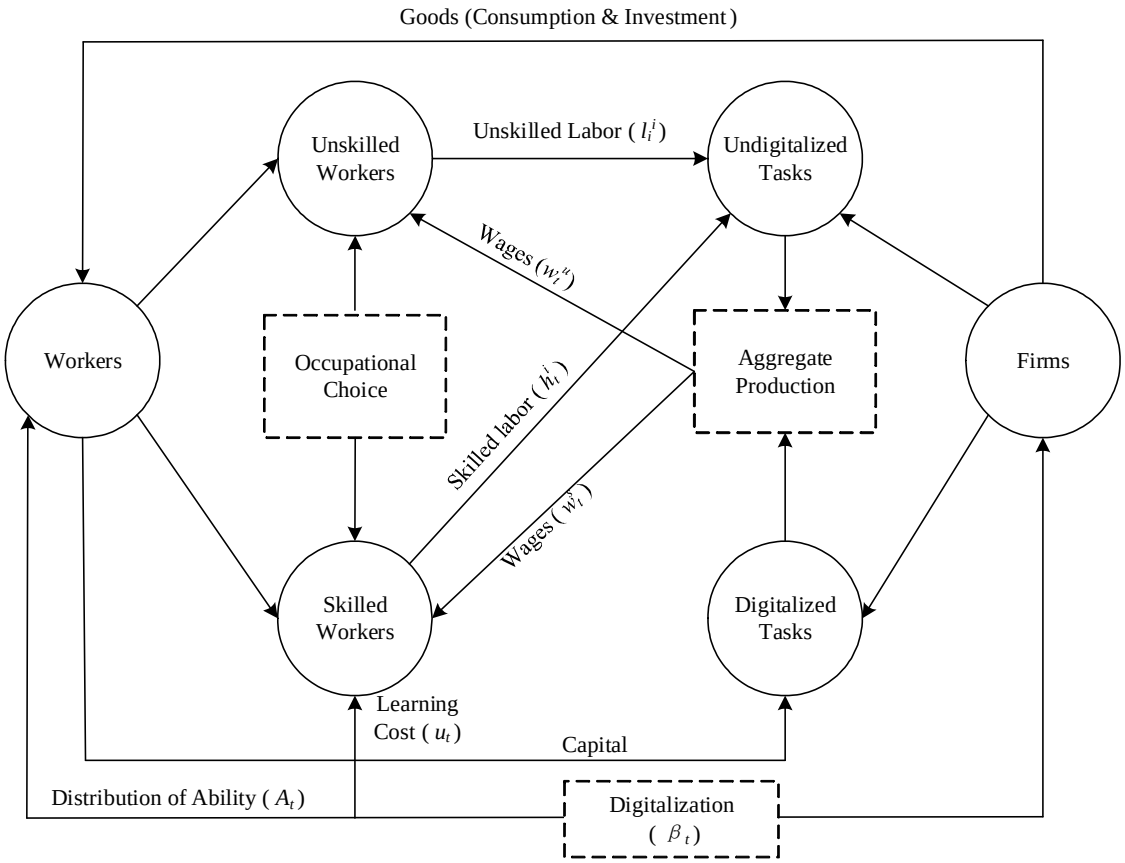


Figure 5: Model Structure

4.2 Production, Digitalization and Labor Demand

We assume that competitive firms produce final goods Y_t by combining different intermediate goods Y_{it} manufactured through different tasks via a constant elasticity of substitution (CES) production function:

$$Y_t = \widetilde{A}\left(\int_0^1 Y_{it}^{\rho} di\right)^{1/\rho} \tag{4}$$

where $\widetilde{A}$ is exogenous total factor productivity or common knowledge, $\frac{1}{1-\rho}$ captures elasticity of substitution across intermediate goods produced by different tasks. When $\rho < 0$, we have $\frac{1}{1-\rho} < 1$ thus different intermediate goods are complements rather than substitutes.

Each task has two options of production:

$$Y_{it} = \begin{cases} L_{it}, \text{ for un-digitalized task} \\ Z_t K_{it}, \text{ for digitalized task} \end{cases} \tag{5}$$

where L_{it} is composite labor supplied by both skilled and unskilled workers, K_{it} is capital used in production for digitalized task and Z_t represents a capital-augmenting technology. Examples of Z_t are technologies to create better machines, better digital devices and

platforms, higher computer power, etc. The way Z_t enters the production function for digitalized task allows for the existence of balanced growth path (shown below), following Grossman *et al.* (2017) and Aghion *et al.* (2018).

Market clearing of factors market requires that:

$$\int_0^1 K_{it} di = K_t$$

$$\int_0^1 L_{it} di = L_t$$

$$Y_t = C_t + I_t = (1-s) Y_t + sY_t$$

Define β_t as the rate of digitalization, it is shown that when factors are optimally utilized, the aggregation (4) can be written as

$$Y_t = \widetilde{A} \left[\beta_t \left(\frac{Z_t K_t}{\beta_t} \right)^{\rho} + (1-\beta_t) \left(\frac{L_t}{1-\beta_t} \right)^{\rho} \right]^{1/\rho} \tag{6}$$

Therefore, there are two forms of factor-augmenting technology in the economy, one is capital-augmenting technology Z_t, the other is digitalization. As noted by Aghion *et al.* (2018), this social production has the property that digitalization β_t is capital-depleting while labor-augmenting. This point is evident if we rewrite it in Cobb-Douglas type form:

$$Y_t = A_t \left[(Z_t B_t K_t)^{\rho} + (C_t L_t)^{\rho} \right]^{1/\rho} \tag{7}$$

with $B_t = (\beta_t)^{\frac{1-\rho}{\rho}}$ and $C_t = (1-\beta_t)^{\frac{1-\rho}{\rho}}$. Because $0 < \beta_t < 1$ and $\rho < 0$, B_t actually decreases in β_t while C_t increases in β_t. This is why Z_t is introduced, i.e., it offers the opportunity to augment capital to offset the depleting effect of digitalization to deliver a BGP.

The shares of capital and labor income in total output are given by:

$$\alpha_{K_t} = \frac{MPK_t \cdot K_t}{Y_t} = \widetilde{A}^{\rho} \beta_t^{1-\rho} \left(\frac{Z_t K_t}{Y_t} \right)^{\rho} \tag{8}$$

$$\alpha_{L_t} = \frac{MPL_t \cdot L_t}{Y_t} = \widetilde{A}^{\rho} (1-\beta_t)^{1-\rho} \left(\frac{L_t}{Y_t} \right)^{\rho} \tag{9}$$

respectively. Thus the ratio of the two share is

$$\frac{\alpha_{K_t}}{\alpha_{L_t}} = \left(\frac{\beta_t}{1-\beta_t} \right)^{1-\rho} \left(\frac{Z_t K_t}{L_t} \right)^{\rho}. \tag{10}$$

PROPOSITION 1 (Existence of balanced growth path): *For* $0 < \beta_t < 1$, $n = 0$ *and* $\rho < 0$, *the economy achieves balanced growth path if either:*

a) $g_{Z_t} = 0$ *and* $\beta_t \longrightarrow 1$*, which is an asymptotic BGP (we name it BGP 1 in what follows) that delivers* $g_{k_t} = g_{y_t}$;

b) Or, $g_{Z_t} = 0$ *and* $\beta_t < 1$*, which is a special case of zero growth economy:* $g_{k_t} = g_{y_t} = 0$;

c) Or, $g_{Z_t} > 0$ *and* $g_{Z_t} = g_{k_t}(1-\beta_t)/\beta_t$*, which delivers is a BGP (we name it BGP 3 in what follows) with* $g_{k_t} = g_{y_t}$.

Proof of PROPOSITION 1: See Appendix A.1.

Discussion.

Case b) implies an economy without growth, thus is discarded.

Case a) and BGP 1 requires minimal assumption about capital-augmenting technology (i.e., a constant Z_t), e.g.,

$$Z_t = 1$$

while Case c) and BGP 3 amounts to imposing a endogenous process for Z_t,

$$Z_t = e^{t\cdot\psi\cdot g_{Z_t}}, \text{ with } g_{Z_t} = g_{k_t}(1-\beta_t)/\beta_t \tag{11}$$

such that it moves in the opposite direction of digitalization β_t.

Therefore, Case c) is a general case for Case a) (By setting $\psi = 0$, we move back to to Case a). In what follows, we will focus on Case c) and BGP 3 take it as our benchmark case.

On BGP, the growth rates are given by:

$$\begin{aligned} g_{Z_t} &= \left(\frac{\rho-1}{\rho}\right) g_{\beta_t}. \\ g_{k_t} &= g_{y_t} = \left[\frac{(\rho-1)\beta_t}{\rho(1-\beta_t)}\right] g_{\beta_t}. \end{aligned}$$

4.3 Human Capital, Ability and Learning Cost

The above specification of production function borrows from the automation literature. The shortcoming of it however, is that it implies monotonic positive relationship between digitalization and wage income. This is consistent with experiences of western countries but China. Therefore, we introduce heterogeneity of labor force following Galor and Moav (2000) such that we can use it as a framework to analyze wage inequality between skilled and unskilled workers. Moreover, we extend the model in two dimensions to capture potential nonlinearity of the relationship between wage gap and digitalization: i) introducing learning cost for people who intend to become skilled workers, and ii) a erosion effect of digitalization on labor share and then on the distribution worker abilities.

Labor demand. Assume that workers are free to choose to become skilled or unskilled workers at time t, thus the total labor force is a combination of them. However, the labor demand is skill-biased under digitalization, i.e., firms total employment is given by:

$$L_t = \gamma h_t + (1 - \delta\beta_t)\, l_t \tag{12}$$

where $\gamma > 1$ represents the higher preference for skilled labor and $0 < \delta < 1$ captures the discrimination of unskilled labor by firms when digitalization is present. The above setting of aggregate labor composition reflects the literature on skill-biased technical change.

Wages. The general wage paid to labor is given by the marginal product of labor:

$$w_t = MPL = \widetilde{A}^{\rho}\left[(1 - \beta_t)\,\frac{Y_t}{L_t}\right]^{1-\rho} = \widetilde{A}^{\rho} w\left(k_t, \beta_t\right) \tag{13}$$

with $y_t = \frac{Y_t}{L_t}$, $k_t = \frac{K_t}{L_t}$.

Given the composition labor in (12), the wage paid to a skilled worker is given by:

$$w_t^s = \gamma \widetilde{A}^{\rho} w\left(k_t, \beta_t\right) \tag{14}$$

and the wage paid to an unskilled worker is given by

$$w_t^u = (1 - \delta\beta_t)\, \widetilde{A}^{\rho} w\left(k_t, \beta_t\right) \tag{15}$$

Ability, learning cost and human capital accumulation. Both skilled and unskilled workers can accumulate human capital to increase h_t and l_t. They differ however, in endowed abilities and learning costs. Firstly, the unskilled workers accumulate human capital according to:

$$l_t^i = 1 - \left(1 - a_t^i\right)\beta_t \tag{16}$$

whilst skilled workers accumulate human capital according to:

$$h_t^i = (1 - \tau)\left[a_t^i - \left(1 - a_t^i\right)\beta_t\right] \tag{17}$$

where a_t^i is realized abilities from a uniform distribution between the region of $a_t^i \in [A_t - 1, A_t]$. When a worker chooses to become a skilled one, he/she must spend a fraction of time, τ to learn high skills that complement with digitalization, so the working time reduces to $(1 - \tau)$. Comparing (16) and (17), we see that both workers human capital are eroded by digitalization by $(1 - a_t^i)\,\beta_t$. However, ability a_t^i can partially offset this erosion effect by extent of $a_t^i\beta_t$ - a augmenting effect. Of course, skilled workers can accumulate more human capital than unskilled workers.

The above setting is not enough to generate nonlinear relationship between digitalization and wage inequality. To do so, we make two extensions:

i) skilled workers pay learning costs given by

$$\mu\left(w_t, \lambda_t, \beta_t\right) = -\frac{\eta}{2}\widetilde{A}^{\rho} w\left(k_t, \beta_t\right) e^{\lambda_t}\left(\beta_t - \overline{\beta}\right)^2. \tag{18}$$

This first extension stems from the notion that workers have to pay learning costs before they become skilled ones. Examples of learning costs can be education costs, tuition fees and training costs for studying digital technology. Effectively, the existence of learning cost imposes transition costs (see, e.g., Cortes and Gallipoli 2018) on labor mobility and makes two groups of labor imperfect substitutes. The function form in (18) borrows from the finance literature, e.g., portfolio adjustment cost. The part e^{λ_t} is introduced as an exogenous AR(1) shock process which captures any financial friction happening during learning, e.g., whether/to what extent workers can borrow to pay tuition fees. A fall in λ_t represents improvement of financial conditions and lower financial costs for learning.

ii) The distribution of worker ability (A_t) evolves with progress in both common technology and digital technology:

$$A_t = \widetilde{A} - \widetilde{\phi}\left(\beta_t\right), \tag{19}$$

That is, general TFP improvement $\widetilde{A}$ help workers complish their jobs more easily. However, on the other hand, digitalization requires more trainings of both skilled and unskill workers who now have to take more trainings to catch up with digitalization[8]. One might think that digitalization reduces ability of unskilled workers while benefits skilled workers. However, this turns out not be true for digitalization. For example, recent work by Brynjolfsson et. al. (2023) find evidence that the use of generative AI disseminates the tacit knowledge of more skilled workers, making them more substitutable and thus less important to firms. For another example, digitalization also has replacement effect on high-skill worker. As a result, high-skill jobs may shrink and turn into low-skill jobs. China now has near 100 million take-away riders, many of whom were white-collar workers with bachelor or higher degrees.

It is noted that $\widetilde{\phi}\left(\beta_t\right)$ is only a general form. There are alternative ways to pin down a specific form for it. One complicated way to go is to think about some mediators through which digitalization can finally take effect on worker ability. An candidate would be capital and labor shares α_{K_t}, α_{L_t}. That is, if digitalization raises $\alpha_{K_t}/\alpha_{L_t}$, it reduces the importance of labor as a whole as a result of substitution effect or as it causes workers loose part

[8] An alternative treatment would be assuming that as digitalization deepens, they hurt high-skilled workers even more than low-skilled workers, thus imposing asymmetric ability erosion effects to two groups of workers. Whilst this may be possible for latest digital technologies such as the adoption of a generative AI, we discard this alternative treatment for two reasons. The first reason is that it is hard to judge the degree of asymmetry. Secondly, workers in most of our sample period did not see the latest development of generative AI.

of their abilities during unemployment. In this case, $\widetilde{\phi}(\beta_t)$ may be further represented as a function of $\alpha_{K_t}/\alpha_{L_t}$:

$$A_t = \widetilde{A} - \widetilde{\phi}\left(\alpha_{K_t}/\alpha_{L_t}\right). \tag{20}$$

Since factor shares are ultimately functions of β_t and $Z_t K_t$, adoption of this form requires tracking dynamic changes in these variables before evaluating how they affect worker ability distribution A_t.

Alternatively, a simplier option is to follow a simple linear rule as in Acemoglu and Restrepo (2018). Specifically, they specify an evolution rule for productivity when there is automation technology $I(t)$:

$$n_t = N_t - I_t$$

That is, creation of new tasks, N_t (which is analogous to our general technology $\widetilde{A}$) raises productivity n_t while new automation technology I_t (which is analogous to our digitalization β_t) reduces it. Following their idea, a simplified rule for (19) can be given by[9]:

$$A_t = \widetilde{A} - \phi\beta_t. \tag{21}$$

We will consider both forms of (20) and (21) in numerical simulations, but only consider (21) when deriving analytical results.

4.4 Labor Income and Occupational Choice

Wage incomes of two groups. Income of skilled workers net of learning cost:

$$I_t^{i,s_net} = I_t^{i,s} - \mu\left(w_t, \lambda_t, \beta_t\right) = w_t^s h_t^i - \mu\left(w_t, \lambda_t, \beta_t\right)$$

Threshold (division of skilled vs unskilled workers):

Workers will choose to be skilled workers (get education/learning/training and pay cost) if and only if:

$$I_t^{i,s_net} \geq I_t^{i,u} \tag{22}$$

The threshold then is derived when the incomes of two options take equal sign:

$$\begin{aligned} & \gamma Z_t w\left(k_t, \beta_t\right)(1-\tau)\left[a_t^i - \left(1-a_t^i\right)\beta_t\right] + \frac{\eta}{2} Z_t w\left(k_t, \beta_t\right) e^{\lambda_t}\left(\beta_t - \overline{\beta}\right)^2 \\ = \;& \left(1-\delta\beta_t\right) Z_t w\left(k_t, \beta_t\right) \cdot \left[1 - \left(1-a_t^i\right)\beta_t\right] \end{aligned}$$

$$\begin{aligned} & \left[a_t^i - \left(1-a_t^i\right)\beta_t\right] + \frac{\eta}{2} e^{\lambda_t}\left(\beta_t - \overline{\beta}\right)^2 \\ = \;& \left(1-\delta\beta_t\right)\left[1 - \left(1-a_t^i\right)\beta_t\right] \end{aligned}$$

[9]By setting $\phi = 0$ in (19), we can switch off this endogenous labor ability channel, and by setting $\psi = 0$ in (11) the same time, we go back to the classical case as in Galor and Moav (2000).

which solves for a_t^*: (we set $\gamma(1-\tau)=1$ as in Galor and Moav 2000)

$$a_t^* = \frac{\left(1-\delta\beta_t+\delta\beta_t^2\right)-\frac{\eta}{2}e^{\lambda_t}\left(\beta_t-\overline{\beta}\right)^2}{\left(1+\delta\beta_t^2\right)} \tag{23}$$

PROPOSITION 2 *(Occupational choice): Given meaningful parameter values, workers occupational choice is determined by the threshold in (23). Workers whose abilities above this threshold choose to be skilled workers, the remaining workers choose to be unskilled workers. And the threshold has the following relation to digitalization:*

a) The threshold, a_t^* is independent with the distribution of worker ability is fixed or not. That is, BGP 1 and BGP 3 deliver the same result since, capital-augmenting technology Z_t, if exists, does not affect worker ability distribution A_t.

b) The relationship between threshold, a_t^* and *digitalization, β_t* is linear (negative) when skilled and unskilled jobs are perfect substitutes (no learning cost), and is irrelevant to changes in distribution of worker ability.

c) *The relationship between threshold, a_t^** and *digitalization, β_t* is nonlinear *(inverted U-shaped) if there is quadratic learning cost which makes skill and unskilled jobs imperfect substitutes.*

Proof of PROPOSITION 2: See Appendix A.2.

$$\begin{aligned}\frac{\partial a_t^*}{\partial \beta_t} &= \frac{\overbrace{\left(-\delta+\delta^2\beta_t^2\right)}^{\text{monotonic(negative)}}+\overbrace{\frac{\eta}{2}e^{\lambda_t}\left(\beta_t-\overline{\beta}\right)^2}^{\text{U-shape}}-\overbrace{\eta e^{\lambda_t}\left(\beta_t-\overline{\beta}\right)}^{\text{monotonic}}}{\left(1+\delta\beta_t^2\right)^2} \\ &= \frac{\overbrace{\left(-\delta+\delta^2\beta_t^2\right)}^{\text{monotonic(negative)}}+\overbrace{\eta e^{\lambda_t}\left(\beta_t-\overline{\beta}\right)\left(\frac{\beta_t-\overline{\beta}}{2}-1\right)}^{\text{U-shape}}}{\left(1+\delta\beta_t^2\right)^2}\end{aligned}$$

We can see that when there is no learning cost ($\eta=0$ in 18), digitalization only leads to negative and monotonic changes in threshold a_t^*. In contrast, if learning cost is present ($\eta>0$), both monotonic and U-shape (second order polynomial of β_t) are present. It is easy to verify that the addition of a linear polynomial with a quadratic polynomial will yield a second order polynomial because the second derivative of the latter will always be nonzero. Thus, we will have a U-shaped relationship in the end, so c) in PROPOSITION 2 is proved.

4.5 Labor Income Inequality

We explore wage income inequalities that are *observable* in data: $i^S(\cdot)$ and $i^U(\cdot)$. The variations in learning costs are not directly observable in real world. Then, we compute three measures of these observable income inequalities: average wage income inequality *between* two groups of workers, *within-group* inequalities of skilled workers and *within-group* inequality of unskilled workers, and examine how they are affected by changes in digitalization β_t.

4.5.1 Between-group inequality

First of all, the *average* income of skilled workers is given by:

$$\begin{aligned}\widetilde{I}_t^S &= \frac{i^S(A_t)+i^S(a_t^*)}{2} \\ &= W_t\frac{\overbrace{a_t^*}^{\text{Labor supply effect}} + A_t - \overbrace{(2-A_t-a_t^*)\beta_t}^{\text{Labor demand effect } a_t^*\beta_t}}{2}\end{aligned}$$

In a similar way, average income of unskilled workers is given by:

$$\begin{aligned}\widetilde{I}_t^U &= \frac{i^U(A-1)+i^U(a_t^*)}{2} \\ &= W_t(1-\delta\beta_t)\frac{2-(3-A_t-a_t^*)\beta_t}{2}\end{aligned}$$

Therefore, *between-group* wage inequality can be obtained:

$$\sigma_t^{\frac{S}{U}} = \frac{\widetilde{I}_t^S}{\widetilde{I}_t^U} = \frac{a_t^*+A_t-(2-A_t-a_t^*)\beta_t}{(1-\delta\beta_t)[2-(3-A_t-a_t^*)\beta_t]}. \tag{24}$$

Given the above formulas of various measures of wage income inequalities, we can see that those inequality measures are not only a direct function of digitalization β_t, but also functions of the worker ability upper bound A_t and the threshold of worker ability a_t^*. Since A_t and a_t^* are also functions of digitalization (see equation 19 and 23), those wage income inequalities are ultimately a function of digitalization β_t. Based these observations, we propose proposition 3.

PROPOSITION 3 *(Digitalization and between-group wage inequality): In this economy,*

a) Increases in digitalization, β_t always monotonically widen between-group wage inequality with fixed distribution of worker ability and frictionless labor mobility;

b) The impact of increases in *digitalization, β_t on between-group wage inequality is nonlinear (inverted U-shaped) if EITHER one of the assumptions is relaxed: i.e., i) when*

worker ability region shrinks (linearly) after digitalization; Or ii) there is quadratic learning cost which makes skill and unskilled jobs imperfect substitutes;

c) The inequality-reducing effect is stronger when the economy is in BGP3 than in BGP1 due to the existence of capital-augmenting technology which further shrinks worker ability region and thus reinforces the inequality-reducing role of digitalization.

PROOF of PROPOSITION 3: See Appendix A.3.

Here presents some key elements of proof. Consider first the case that there is endogenous adjustment of worker ability ($\psi > 0$ & $\phi > 0$) but without learning cost ($\eta = 0$). We can examine the impact of digitalization β_t on between-group wage income inequality $\sigma_t^{\frac{S}{U}}$ by taking first order derivative of the latter to the former.

$$\frac{\partial \sigma_t^{\frac{S}{U}}}{\partial A_t} = \frac{2 - \beta_t + [2A_t - \beta_t]\,\beta_t}{(1 - \theta\beta_t)\left\{[2 - (3 - A_t - a_t^*)\,\beta_t]\right\}^2}$$

It is clear that $\frac{\partial \sigma_t^{\frac{S}{U}}}{\partial A_t}$ is a first order function of A_t and its second order $\frac{\partial \sigma_t^{\frac{S}{U}}}{\partial A_t \partial A_t}$ is positive. It is deduced that A_t can bring hump-shaped impact on between-group wage income inequality $\sigma_t^{\frac{S}{U}}$. Further, since from (19): $A_t = \widetilde{A} - \phi\beta_t$, we know that $\frac{\partial A_t}{\beta_t} = -\phi$. Summarizing these findings conclude that the introduction of endogenous distribution of worker ability results in an inverted U-shaped impact of β_t on $\sigma_t^{\frac{S}{U}}$.

Next, consider the case that there is positive learning cost ($\eta > 0$) but no endogenous adjustment of worker ability ($\psi = 0$ & $\phi = 0$). In this case, only learning cost channel is in play. However, since the learning cost $\mu(w_t, \lambda_t, \beta_t)$ only appears in the threshold a_t^*, we can easily check the nonlinearity between $\sigma_t^{\frac{S}{U}}$ and learning cost $\mu(w_t, \lambda_t, \beta_t)$ by examining the first and second derivative of $\sigma_t^{\frac{S}{U}}$ to a_t^*. It is easily verified that the first derivative of $\sigma_t^{\frac{S}{U}}$ to a_t^* are identical to the first derivative of $\sigma_t^{\frac{S}{U}}$ to A_t above.

This result demonstrates that $\sigma_t^{\frac{S}{U}}$ increases in a_t^*. Then, combining this result with the finding in PROPOSITION 2 that $\frac{\partial a_t^*}{\partial \beta_t}$ has an inverted U-shaped relationship with β_t, we conclude that the relationship between β_t and $\sigma_t^{\frac{S}{U}}$ is also inverted U-shaped. It is noted that the way learning cost leading to hump-shaped responses of $\sigma_t^{\frac{S}{U}}$ replies totally on the mediating effect of the nonlinear relationship between β_t and a_t^*. In contrast, the way endogenous worker ability A_t leading to hump-shaped responses of $\sigma_t^{\frac{S}{U}}$ replies totally on the nonlinear relationship between A_t and $\sigma_t^{\frac{S}{U}}$ directly. This is why we test particularly the mediating effect empirically in section 2.

4.5.2 Within-group inequality

Differently, *within-group* wage inequality is defined as the ratio between maximum wage income to minimum wage income in a particular group. Given this definition, the *within-group* of skilled workers is computed as:

$$\sigma_t^S = \frac{i^S(A_t)}{i^S(a_t^*)} = \frac{A_t - (1 - A_t)\beta_t}{a_t^* - (1 - a_t^*)\beta_t}. \tag{25}$$

Similarly, *within-group* wage inequality of unskilled workers is computed as:

$$\sigma_t^U = \frac{i^U(a_t^*)}{i^U(A_t - 1)} = \frac{1 - (1 - a_t^*)\beta_t}{1 - (2 - A_t)\beta_t}. \tag{26}$$

PROPOSITION 4 *(Digitalization and within-group wage inequality): In this economy,*

a) Digitalization, β_t increases within group inequality of both workers **when** *the distribution of worker ability* A_t *is fixed, and does not depend on the existence of learning cost,* η;

b) Digitalization, β_t increases within group inequality of unskilled workers but reduces group inequality of skilled workers **when** *the distribution of worker ability* A_t *is endogenous.*

c) The impact of ability distribution A_t *on within-group wage inequality is stronger when considering BGP3 than BGP1.*

PROOF of PROPOSITION 4: See Appendix A.4.

4.5.3 Understanding the effect of worker ability distribution

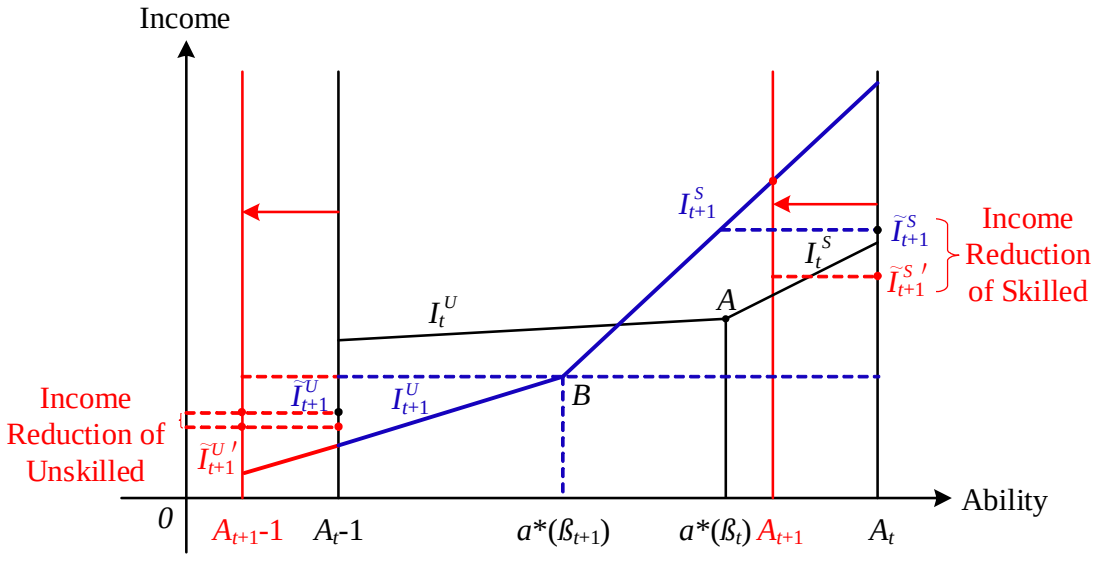


Figure 6: The effect of a fall in worker ability distribution

The implication of this workers overall ability ceiling evolution rule is that, other things equal, progress in digital technology reduces workers ability as a whole and so do wages of two groups. This put downward pressure on wage ineqaulity as the reduction in wages of skilled workers is much more than those of unskilled workers. This can be dipicted in Figure 6 where the black vertical lines represent the distribution of worker ability at time t and the two red vertical lines represent the distribution of worker ability at time t after digitalization evolves. We can see that, despite the fall of threshold thus more workers could have become skilled workers, the reduced level of worker ability distribution should offset the enlarging wage income inequality. Therefore, we introduce counterveiling forces that could potentially create a nonlinear (inverted-U) relationship between digitalization and wage income inequality.

4.6 Summary of Several Countervailing Effects

Positive effects on inequality:

1. Productivity effect (Direct effect on labor demand):

$$\beta_t \uparrow \Longrightarrow I_t^{i,u} \uparrow, I_t^{i,s} \uparrow$$

2. SBTC (Another direct effect on labor demand):

$$\begin{aligned} L_t &= \gamma h_t + (1 - \delta\beta_t)\, l_t \\ \gamma &> 1,\ \delta\beta_t < 1 \end{aligned}$$

3. Ability-augmenting effect (Indirect effect on labour demand):

$$\left(a_t^i \beta_t\right) \uparrow$$

Negative effects on inequality:

1. Creative destruction (Direct effect on all workers):

$$l_t^i = 1 - \left(1 - a_t^i\right) \beta_t$$

$$h_t^i = (1 - \tau) \left[a_t^i - \left(1 - a_t^i\right) \beta_t\right]$$

Nonlinear effects on inequality:

1. *Learning cost channel* (Mediating effect on labor supply and wage inequality):

$$I_t^{i,s} - \mu\left(w_t, \theta_t, \beta_t\right) \geq I_t^{i,u}$$

$$\mu\left(w_t, \lambda_t, \beta_t\right) = -\frac{\eta}{2} Z_t w\left(k_t, \beta_t\right) e^{\lambda_t} \left(\beta_t - \overline{\beta}\right)^2$$

2. *Worker ability channel* (Direct effect on labor supply and wage inequality):

$$A_t = \widetilde{A} - \widetilde{\phi}\left(\beta_t\right).$$

5 Simulations

5.1 Parameter Values

Before simulating the model specified in last section, we discuss about calibration of parameters. The erosion of labor parameter δ takes value of 0.25. This is most commonly used value for example in the evolution of capital literature in macroeconomics. The natural rate of interest rate, or the long-run real interest rate is 2 percent which matches the average real interest rate in China. It is also close to values usually adopted for western countries. The parameter η which governs the size of learning cost is calibrated to 10 as the benchmark. It is hard to pin down this value from literature for the Chinese economy. Therefore, I follow the estimate of a similar parameter in western countries. We vary this parameter from 0 to 20 to check robustness. The parameter λ is set to 1 in benchmark case for minimum financial friction. The reflection point of digitalization is set to 0.25 according to the average digitalization in data. The parameter ϕ is the coefficient on work ability which captures the impact of digitalization on work ability upper bound. It can be set to 0 to mute off this channel. Finally, ψ is set to 1 for positive and capital-augmenting technology growth rate and to 0 for constant capital-augment technology. The calibration is summarized in Table 3.

Table 7: Parameter values

Parameters	Value	Definition	Region
δ	0.25	Erosion of labor	[0, 0.75]
$\overline{r}$	2%	Natural rate of interest rate	[1%, 8%]
η	3	Size of learning cost	[0, 20]
λ	1	Financial friction	[1, 5]
$\overline{\beta}$	0.25	Reflection point	[0.1, 0.5]
ϕ	0 or 1	Coefficient of erosion effect on work ability	0 or 1
ψ	0 or 1	Coefficient on capital-augmenting technology growth	0 or 1

5.2 In-between Wage Inequality During Digitalization

We first look at the results of simulations for a inverted U-shaped relationship between digitalization and in-between group wage income inequality. Firstly, the result under fixed distribution of worker ability ($\psi = \phi = 0$) and positive learning cost ($\eta > 0$) is reported in Figure 7. The horizontal axis is exogenous changes in digitalization from 0 to 50%.

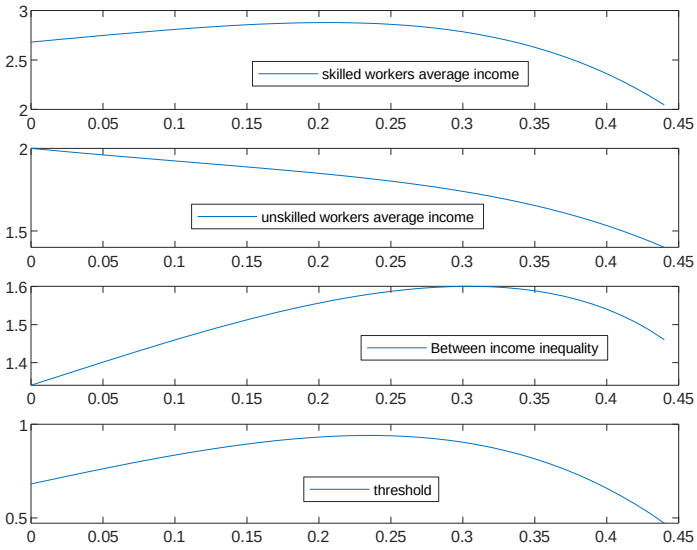


Figure 7: Simulation of in-between wage inquality during digitalization (fixed distribution of worker ability ($\psi = \phi = 0$) and postive learning cost ($\eta > 0$)).

It is seen that the model successfully generates hump-shaped responses of average wage income of skilled workers, threshold of skilled worker and wage income inequality between skilled and unskilled workers. As discussed in PROPOSITION 2 and 3, the force that deliveries this nonlinearity totally replies on the hump-shaped responses of the threshold due to the existence of learning cost. The intuition is that, workers find it increasingly difficult to follow new digital technology during the early stage of digitalization, they have to bear high costs of learning and trainings before they can become skilled workers. This is common for any new technology adoption in past one hundred years. However, as digitalization deepens and infrastructure is built ready, the positive effect and scale effect come into play. Workers now will take advantage of the positive externality of digital technology, and are able to work on digital platforms as takeaway riders, live video makers, express delivery workers and even internet pop stars. The learning cost is now much reduced and requires less and less start-up costs. Therefore, the threshold of becoming skilled workers begin to fall, allowing unskilled workers to transform into skilled workers.

As shown in the introduction section, this conjecture is supported by the large falls of labor in traditional manufacturing sector and substantial flow-ins for the data-related sectors, especially for the time period after 2012.

Now turn to the case that the distribution of worker ability is endogenously determined by digitalization and capital-augmented technology growth ($\psi > 0, \phi > 0$) and zero learning cost ($\eta = 0$). The results are reported in Figure 8.

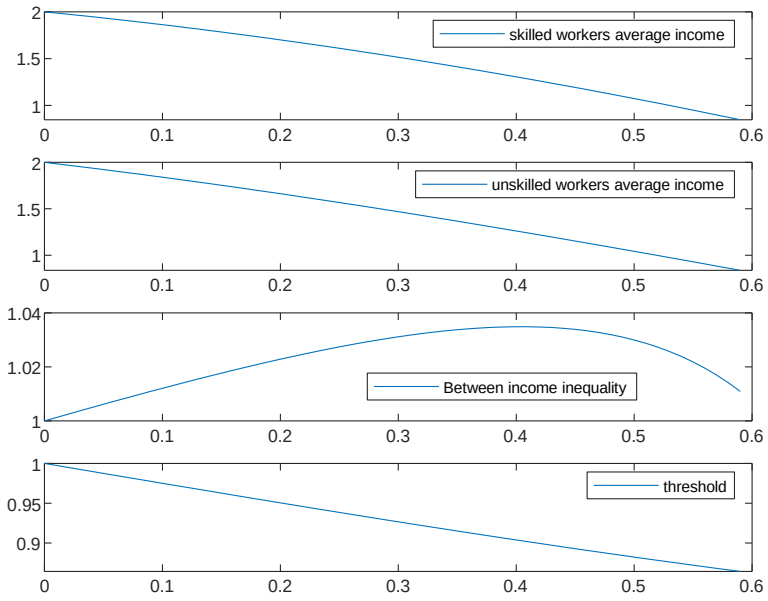


Figure 8: Simulation of in-between wage inquality during digitalization (endogenous distribution of worker ability ($\psi > 0, \phi > 0$) and zero learning cost ($\eta = 0$)).

Compared with Figure 7, the key difference is that now the dynamic responses of the threshold is almost monotonic. Thus, the learning cost solely accounts for the hump-shaped responses of between-group wage income inequality. This illustrates the importance of the distribution of worker ability: although the threshold is lowered so that more unskilled workers can become skilled workers, it comes at a cost of falling average wages for both groups. This endogenous worker ability channel thus points out the importance of learning following a technology emergence, and potential desires aid public policy.

5.3 Within Group Wage Inequality During Digitalization

This subsection further diagnoses the within-group inequalities to better understand what happens to labor market structure during digitalization. First of all, the within-group wage income inequality of skilled and unskilled worker are plotted in the first two panels

in Figure 9. for the case of fixed distribution of worker ability ($\psi = \phi = 0$) and positive learning cost ($\eta > 0$). When the learning cost channel is the main mechanism at play, the wage dispersions of both skilled and unskilled are widened. This is not surprising given that the erosion effect of digitalization is minimized and the threshold has been increasing until reflection point is reached. For the skilled group, the number of bottom workers are increasing, but the new comers can only enjoy low wages because their abilities are lower. Thus, the gap of their wage income with top earners in the same group are enlarged. For the unskilled group, more and more skilled workers come into this unskilled group in the first stage of increasing threshold, so the top earners in the unskilled group are changing every time period, responsible for the rising within-group wage gap. This wage gap continues to expand after the reflection point because the opportunity cost of labor is raised up by digitalization for workers who choose to stay in the unskilled group.

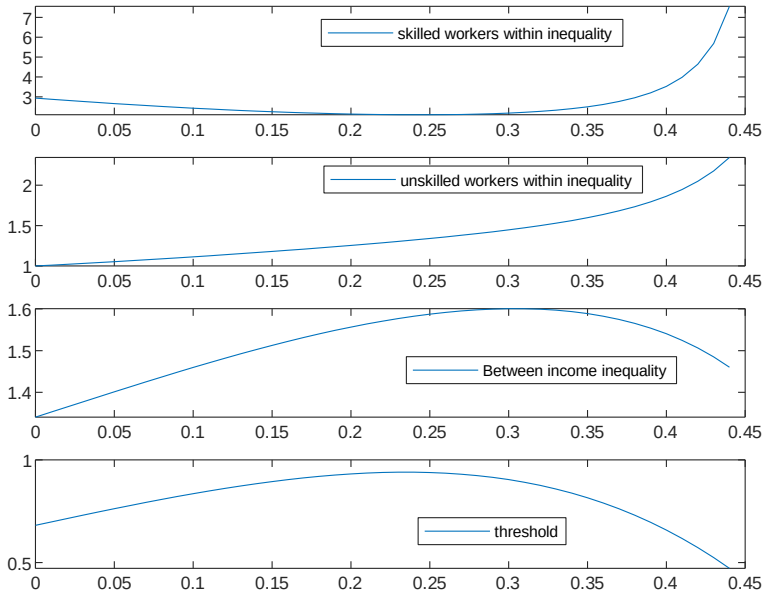


Figure 9: Simulation of within-group wage inquality during digitalization (fixed distribution of worker ability ($\psi = \phi = 0$) and postive learning cost ($\eta > 0$)).

Next, the within-group wage income inequality of skilled and unskilled worker are plotted in the first two panels in Figure 10. for the case of endogenous distribution of worker ability ($\psi > 0, \phi > 0$) and zero learning cost ($\eta = 0$).

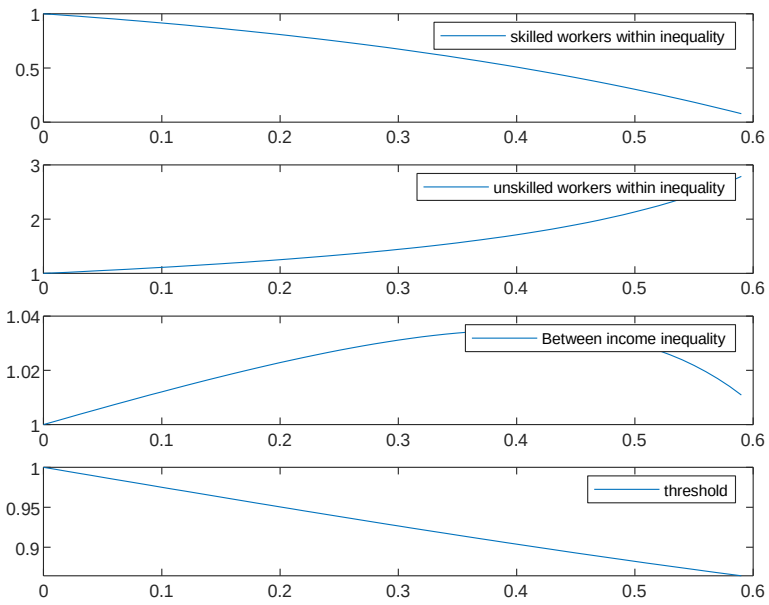


Figure 10: Simulation of within-group wage inquality during digitalization (endogenous distribution of worker ability ($\psi > 0, \phi > 0$) and zero learning cost ($\eta = 0$)).

Compared with Figure 9, the key difference is that now within group wage gap is decreasing rather than increasing. This interesting result is explained as follows. When learning cost is eliminated, digitalization now causes less fall in threshold (recall that ability upper bound A_t does not affect a_t^* at all). This means that top worker ability is reduced at minimal impact on bottom skilled workers, so for the fall in within-group wage gap. The same logic can explain the rising wage gap within the unskilled group - because the threshold is less affected, the top earners in the unskilled group still earn a lot while the bottom workers in the unskilled group suffer a drop in ability and thus the wage gap within this unskilled group is widened. This result has important implication for public policy: those bottom workers who are flourished with new digital technology find themselves hard to catch up. As time goes, their ability and skills deteriorate. In this sense, provision of low cost training programs would be the key to help them survive in the digital era.

6 Concluding Remarks

In light of the rising income inequality across the globe since 1980s, researchers have made various explanations, many of which have acknowledged the role of the adoption of new technologies in widening wage gaps between groups. We revisit this issue by providing a new set of empirical evidence in the Chinese economy in terms of the relationship between

digitalization and wage income inequality. We find that this relationship is inverted U-shaped rather than monotonic. To reconcile this new evidence with traditional views, we propose a task-based growth model with human capital accumulation, heterogenous workers and endogenous occupational choice. We propose two mechanisms that can account for hump-shaped relationship between wage income inequality and digitalization. One is the learning cost channel which states that workers in the economy are initially harmed by digital technology due to high learning cost. But they also benefit from developments of digital economy in later stage when infrastructures are more complete and platforms reduce substantially the cost of learning. Thus, the threshold of becoming skilled workers show an inverted U-shape, which indirectly causes the hump-shaped responses of wage income inequality. The second channel is the worker ability channel which allows for negative creative destruction effect of digitalization on worker ability. The latter shifts the worker ability to the left when digitalization happens but does not affect the threshold of skilled labor. It can also generate an inverted U-shape between digitalization and wage income inequality due to the fact that it weakens the positive contribution of digitalization on inequality.

The two mechanisms we propose above are not *ad hoc*. The learning cost channel, although being novel in digital economy literature, is analogous to the quadratic adjustment costs of financial portfolio decisions in finance literature or the cost of adjusting prices in New Keynesian economics literature. It captures the important insight that digital technologies differ from traditional common technology in that it not only affects labor demand by biasing production cost of firms, but also by changing labor supply of workers and occupational choice due to its externality on learning cost. The worker ability channel, on the other hand, borrows from the recent literature on automation where the creation of new tasks are positively affected by common technology progress but negatively affected by automation. The innovation of our worker ability channel is that it causes endogenous change of worker ability distribution which also cause inverted U-shaped responses of income inequality.

Our paper has important policy implications. The nonlinear relationship between wage income inequality and digitalization indicates that new technology may have both good and bad sides. Understanding both sides at different stages of economic development is critical before drawing conclusions and making policy prescriptions. Our study does support government policy that targets workers with relatively low abilities as they are less likely to be benefited from digitalization even in the long run. Moreover, our study also points out several directions for future research. The two mechanisms may relate to more micro-foundations in finance-related literature and the literature of knowledge. Also,

our research also has implications for studying other forms of new technologies, opening up new perspectives on the economic consequences of them. These leave for future research.

7 References

References

[1] Acemoglu, D. (1998). "Why Do New Technologies Complement Skills? Directed Technical Change and Wage Inequality," *The Quarterly Journal of Economics*, Oxford University Press, vol. 113(4), pages 1055-1089.

[2] Acemoglu, D. and Autor, D. (2011). "Skills, Tasks and Technologies: Implications for Employment and Earnings," Handbook of Labor Economics, in: O. Ashenfelter & D. Card (ed.), *Handbook of Labor Economics*, edition 1, volume 4, chapter 12, pages 1043-1171, Elsevier.

[3] Acemoglu, D., Makhdoumi, A., Malekian, A. and Ozdaglar, A. (2022). "Too much data: Prices and inefficiencies in data markets." *American Economic Journal: Microeconomics*, 14(4), pp.218-256.

[4] Acemoglu, D. and Restrepo, P. (2018). "The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment," *American Economic Review*, American Economic Association, vol. 108(6), pages 1488-1542, June.

[5] Acemoglu, D. and Restrepo, P. (2020). "Robots and Jobs: Evidence from US Labor Markets," *Journal of Political Economy*, University of Chicago Press, vol. 128(6), pages 2188-2244.

[6] Acemoglu D. and Restrepo P. (2022). "Tasks, Automation, and the Rise in U.S. Wage Inequality," *Econometrica*, Econometric Society, vol. 90(5), pages 1973-2016, September.

[7] Aghion, P. (2002) "Schumpeterian Growth Theory and the Dynamics of Income Inequality." *Econometrica*, Vol. 70, No. 3 (May, 2002), 855–882.

[8] Aghion, P., Jones, B. F. and Jones, C. I. (2018). "Artificial Intelligence and Economic Growth." *NBER Chapters*, National Bureau of Economic Research, Inc.

[9] Baron, R.M. and Kenny, D. (1986). "The Moderator-Mediator Variable Distinction in Social Psychological Research: Conceptual, Strategic, and Statistical Considerations." *Journal of Personality and Social Psychology*, 51, 1173-1182.

[10] Bergemann, D., Bonatti, A. and Gan, T. (2022). "The economics of social data." *The RAND Journal of Economics*, 53: 263-296.

[11] Bohm, S., Grossmann, V. and Steger, T. M. (2015). "Does expansion of higher education lead to trickle-down growth?," *Journal of Public Economics*, Elsevier, vol. 132(C), pages 79-94.

[12] Borghans, Lex and ter Weel, B. (2007). "The diffusion of computers and the distribution of wages," *European Economic Review*, Elsevier, vol. 51(3), pages 715-748, April.

[13] Brynjolfsson, E., Li, D. and Raymond, L. R. (2023). "Generative AI at Work," *NBER Working Papers* 31161, National Bureau of Economic Research, Inc.

[14] Castello-Climent, A. & Domenech, R. (2021). "Human capital and income inequality revisited," *Education Economics,* Taylor & Francis Journals, vol. 29(2), pages 194-212, March.

[15] Cong, L. W., Wei, W., Xie, D. and Zhang, L. (2022). "Endogenous growth under multiple uses of data," *Journal of Economic Dynamics and Control*, Elsevier, vol. 141(C).

[16] Cong, L. W., Xie, D. and Zhang L. (2021). "Knowledge Accumulation, Privacy, and Growth in a Data Economy." *Management Science*, 67(10):6480-6492.

[17] Che, Y. & Zhang, L. (2018). "Human Capital, Technology Adoption and Firm Performance: Impacts of China's Higher Education Expansion in the Late 1990s," *Economic Journal*, Royal Economic Society, vol. 128(614), pages 2282-2320, September.

[18] Cheng H., Jia R., Li D., & Li, H. (2019). "The rise of robots in china." *Journal of Economic Perspectives*, vol. 33(2), pages 71-88.

[19] Cortes, G. M. and Gallipoli, G. (2018). "The Costs of Occupational Mobility: An Aggregate Analysis," *Journal of the European Economic Association*, European Economic Association, vol. 16(2), pages 275-315.

[20] Dvorkin, M. and Monge-Nara A. (2019). "On the Dynamics of Occupational Choice, Human Capital Accumulation and Growth," *2019 Meeting Papers 1461*, Society for Economic Dynamics.

[21] Farboodi, M., Matray, A., Veldkamp, L. and Venkateswaran, V. (2022). "Where Has All the Data Gone?," *The Review of Financial Studies*, Volume 35, Issue 7, Pages 3101–3138.

[22] Farboodi M. and Veldkamp, L. (2021). "A Model of the Data Economy," *NBER Working Papers* 28427, National Bureau of Economic Research, Inc.

[23] Frey, C. B. (2020), *The Technology Trap: Capital, Labor, and Power in the Age of Automation*, Princeton University Press.

[24] Ge, S. and Yang, D. T. (2014). "Changes in China's Wage Structure." *Journal of the European Economic Association*, Vol. 12, No. 2, pp. 300-336

[25] Ghosh, P., Valle, B. and Zeng, Y. (2021) "FinTech Lending and Cashless Payments." *Working Paper*.

[26] Goldin, C., and Katz L. F. (2007). "The Race between Education and Technology: The Evolution of U.S. Educational Wage Differentials, 1890 to 2005", *NBER Working Papers* 12984, National Bureau of Economic Research, Inc.

[27] Gomes, F., Jansson, T. and Karabulut, Y. (2022), "Do Robots Increase Wealth Dispersion?" *Working paper*.

[28] Grossman, G. M., Helpman, E., Oberfield, E. and Sampson, T. (2017). "Balanced Growth Despite Uzawa," *American Economic Review*, American Economic Association, vol. 107(4), pages 1293-1312, April.

[29] Galor, O. and Moav, O. (2000). "Ability-Biased Technological Transition, Wage Inequality, and Economic Growth," *The Quarterly Journal of Economics*, Oxford University Press, vol. 115(2), pages 469-497.

[30] Hemous, D. and Olsen, M. (2022). "The Rise of the Machines: Automation, Horizontal Innovation, and Income Inequality," *American Economic Journal: Macroeconomics*, American Economic Association, vol. 14(1), pages 179-223, January.

[31] Ichihashi, S. (2021). "The economics of data externalities," *Journal of Economic Theory*, Elsevier, vol. 196(C).

[32] Jones, C. I. and Tonetti, C. (2019). "Nonrivalry and the Economics of Data," *NBER Working Papers* 26260, National Bureau of Economic Research, Inc.

[33] Kambourov, G. and Manovskii, I. (2008). "Rising Occupational And Industry Mobility In The United States: 1968-97," *International Economic Review*, Department of Economics, University of Pennsylvania and Osaka University Institute of Social and Economic Research Association, vol. 49(1), pages 41-79, February.

[34] Kambourov, G. and & Manovskii, I. (2009). "Occupational Mobility and Wage Inequality," *Review of Economic Studies*, Oxford University Press, vol. 76(2), pages 731-759.

[35] Kasa, K. and Lei, X. (2018). "Risk, Uncertainty and the Dynamics of Inequality," *Journal of Monetary Economics*, 94, 60-78.

[36] Katz, L. F. and Murphy, K. M. (1992). "Changes in Relative Wages, 1963–1987: Supply and Demand Factors," *The Quarterly Journal of Economics*, Oxford University Press, vol. 107(1), pages 35-78.

[37] Korinek, Anton and Megan Juelfs (2022), "Preparing for the (non-existent?) future of work", NBER working paper, No. 30172

[38] Kuhn, P. and Mansour, H. (2014). "Is Internet Job Search Still Ineffective?," *Economic Journal,* Royal Economic Society, vol. 124(581), pages 1213-1233, December.

[39] Kuznets, S. (1955). "Economic Growth andIncomeInequality." *American Economic Review*, 45(1), pp.1-28.

[40] Liu, Z., Sockin, M. and Xiong, W. (2023). "Data Privacy and Algorithmic Inequality," *NBER Working Papers* 31250

[41] Messina, J. and Silva, J. (2019). "Twenty Years of Wage Inequality in Latin America," *IDB Publications (Working Papers)* 9734, Inter-American Development Bank.

[42] Milanovic, B. (2016). *Global Inequality: A New Approach for the Age of Globalization*, Harvard University Press, Belknap Press

[43] Piketty, T. (2014). *Capital in the Twenty-first Century*, Translated by A. Goldhammer, Harvard University Press.

[44] Zeira, J., (1998). "Workers, Machines, And Economic Growth." *Quarterly Journal of Economics*, November 1998, 113 (4), 1091–1117.

8 Appendices

A. Proofs of Propositions

A.1 Proof of PROPOSITION 1

Existence of a BGP requires that factor shares are stable. This implies that:

$$\begin{aligned}\frac{d(\alpha_{K_t})}{\alpha_{K_t}} &= (1-\rho)\frac{d(\beta_t)}{\beta_t} + \rho\frac{d(Z_t)}{Z_t} + \rho\left(\frac{d(K_t)}{K_t} - \frac{d(Y_t)}{Y_t}\right) \\ &= (1-\rho)g_{\beta_t} + \rho g_{Z_t} + \rho(g_{K_t} - g_{Y_t}) = 0\end{aligned}$$

$$\frac{d\left(\frac{\alpha_{K_t}}{\alpha_{L_t}}\right)}{\frac{\alpha_{K_t}}{\alpha_{L_t}}} = (1-\rho)g_{\beta_t} + \rho(1-\beta_t)(g_{K_t} - g_{L_t} + g_{Z_t}) = 0$$

where we use a g_{X_t} function to denote the growth rate of variable X_t. By further making use of $g_{L_t} = n$, $g_{k_t} = g_{K_t} - n$ and $g_{y_t} = g_{Y_t} - n$, we obtain:

$$d(\alpha_{K_t})/\alpha_{K_t} = (1-\rho)g_{\beta_t} + \rho g_{Z_t} + \rho(g_{k_t} - g_{y_t}) = 0 \tag{27}$$

$$d\left(\frac{\alpha_{K_t}}{\alpha_{L_t}}\right) / \left(\frac{\alpha_{K_t}}{\alpha_{L_t}}\right) = (1-\rho)g_{\beta_t} + \rho(1-\beta_t)(g_{k_t} + g_{Z_t}) = 0 \tag{28}$$

which yield:

$$g_{y_t} = \beta_t(g_{k_t} + g_{Z_t}). \tag{29}$$

Three cases of BGP in proposition 1 can be easily implied by (29). Thus, a)-c) are proved.

Combinning (27) and (28), the growth rates on BGP are given by:

$$\begin{aligned}g_{Z_t} &= \left(\frac{\rho-1}{\rho}\right)g_{\beta_t} \\ g_{k_t} &= g_{y_t} = \left[\frac{(\rho-1)\beta_t}{\rho(1-\beta_t)}\right]g_{\beta_t}.\end{aligned}$$

A.2 Proof of PROPOSITION 2

Proof of PROPOSITION 2:

Proof a) can be directly implied from (23) and (19). Proof b) can be derived by taking first order derivative of a_t^* to β_t. Both a) and b) are proved in Galor and Moav (2002).

Proof of c): When the learning cost is present and worker ability upper bound is

endogenous (worker ability distribution is unfixed)

$$\begin{aligned}
\frac{\partial a_t^*}{\partial \beta_t} &= \frac{\partial \left[\left(1-\delta\beta_t+\delta\beta_t^2\right)-\frac{\eta}{2}e^{(1+\lambda\overline{r}t)}\left(\beta_t-\overline{\beta}\right)^2\right]/\partial\beta_t}{\left(1+\delta\beta_t^2\right)} \\
&\quad -\frac{\left(1-\delta\beta_t+\delta\beta_t^2\right)-\frac{\eta}{2}e^{(1+\lambda\overline{r}t)}\left(\beta_t-\overline{\beta}\right)^2}{\left(1+\delta\beta_t^2\right)^2}\frac{\partial\left(1+\delta\beta_t^2\right)}{\partial\beta_t} \\
&= \frac{(-\delta+2\delta\beta_t)-\eta e^{(1+\lambda\overline{r}t)}\left(\beta_t-\overline{\beta}\right)}{\left(1+\delta\beta_t^2\right)} \\
&\quad -\frac{\left(1-\delta\beta_t+\delta\beta_t^2\right)-\frac{\eta}{2}e^{(1+\lambda\overline{r}t)}\left(\beta_t-\overline{\beta}\right)^2}{\left(1+\delta\beta_t^2\right)^2}(2\delta\beta_t) \\
&= \frac{(-\delta+2\delta\beta_t)\left(1+\delta\beta_t^2\right)-\eta e^{(1+\lambda\overline{r}t)}\left(\beta_t-\overline{\beta}\right)}{\left(1+\delta\beta_t^2\right)^2} \\
&\quad -\frac{\left(1-\delta\beta_t+\delta\beta_t^2\right)-\frac{\eta}{2}e^{(1+\lambda\overline{r}t)}\left(\beta_t-\overline{\beta}\right)^2}{\left(1+\delta\beta_t^2\right)^2}(2\delta\beta_t) \\
&= \frac{(-\delta+2\delta\beta_t)\left(1+\delta\beta_t^2\right)-\eta e^{(1+\lambda\overline{r}t)}\left(\beta_t-\overline{\beta}\right)}{\left(1+\delta\beta_t^2\right)^2} \\
&\quad -\frac{\left(1+\delta\beta_t^2\right)(2\delta\beta_t)-\delta\beta_t(2\delta\beta_t)-\frac{\eta}{2}e^{(1+\lambda\overline{r}t)}\left(\beta_t-\overline{\beta}\right)^2}{\left(1+\delta\beta_t^2\right)^2}
\end{aligned}$$

$$\begin{aligned}
\frac{\partial a_t^*}{\partial \beta_t} &= \frac{\overbrace{\left(-\delta+\delta^2\beta_t^2\right)}^{\text{monotonic(negative)}}+\overbrace{\frac{\eta}{2}e^{(1+\lambda\overline{r}t)}\left(\beta_t-\overline{\beta}\right)^2}^{\text{U-shape}}-\overbrace{\eta e^{(1+\lambda\overline{r}t)}\left(\beta_t-\overline{\beta}\right)}^{\text{monotonic}}}{\left(1+\delta\beta_t^2\right)^2} \\
&= \frac{\overbrace{\left(-\delta+\delta^2\beta_t^2\right)}^{\text{monotonic(negative)}}+\overbrace{\eta e^{(1+\lambda\overline{r}t)}\left(\beta_t-\overline{\beta}\right)\left(\frac{\beta_t-\overline{\beta}}{2}-1\right)}^{\text{U-shape}}}{\left(1+\delta\beta_t^2\right)^2}
\end{aligned}$$

We can see that when there is no learning cost ($\eta = 0$ in 18), digitalization only leads to negative and monotonic changes in threshold a_t^*. In contrast, if learning cost is present ($\eta > 0$), both monotonic and U-shape (second order polynomial of β_t) are present. It is easy to verify that the addition of a linear polynomial with a quadratic polynomial will yield a second order polynomial by because the second derivative of the latter will always be nonzero. Thus, we will have a U-shaped relationship in the end, so c) in PROPOSITION 2 is proved.

A.3 Proof of PROPOSITION 3

PROOF of PROPOSITION 3:

Consider first the case that there is endogenous adjustment of worker ability ($\psi > 0$ & $\phi > 0$) but without learning cost ($\eta = 0$). We can examine the impact of digitalization β_t on between-group wage income inequality $\sigma_t^{\frac{S}{U}}$ by taking first order derivative of the latter to the former. Further more, since $\sigma_t^{\frac{S}{U}}$ is a function of a_t^* and A_t, but a_t^* is independent of A_t (see PROPOSITION 2), we can deduce whether $\sigma_t^{\frac{S}{U}}$ is a second order polynomial of β_t by noting that, from the formula of $\sigma_t^{\frac{S}{U}}$,

$$\sigma_t^{\frac{S}{U}} = \frac{\widetilde{I}_t^S}{\widetilde{I}_t^U} = \frac{a_t^* + A_t - (2 - A_t - a_t^*)\,\beta_t}{(1 - \delta\beta_t)\,[2 - (3 - A_t - a_t^*)\,\beta_t]}.$$

we see that:

i) From PROPOSITION 2, a_t^* is a first order polynomial of β_t when learning cost is zero ($\eta = 0$). Thus, a_t^* does not deliver nonlinearity itself.

ii) From (19): $A_t = \widetilde{A} - \phi\beta_t$, A_t is a first order polynomial of β_t. Thus, β_t does not deliver nonlinearity itself.

iii) The products $A_t\beta_t$ and $a_t^*\beta_t$ in the numerator are a second order polynomials of β_t.

ii) The first derivative of $\sigma_t^{\frac{S}{U}}$ to A_t is:

$$\begin{aligned}
\frac{\partial\sigma_t^{\frac{S}{U}}}{\partial A_t} &= \frac{(1+\beta_t)(1-\theta\beta_t)[2-(3-A_t-a_t^*)\beta_t] - (1-\theta\beta_t)\beta_t[a_t^*+A_t-(2-A_t-a_t^*)\beta_t]}{\{(1-\theta\beta_t)[2-(3-A_t-a_t^*)\beta_t]\}^2} \\
&= \frac{(1-\theta\beta_t)\{(1+\beta_t)2-(1+\beta_t)(3-A_t-a_t^*)\beta_t - \beta_t[a_t^*+A_t-(2-A_t-a_t^*)\beta_t]\}}{\{(1-\theta\beta_t)[2-(3-A_t-a_t^*)\beta_t]\}^2} \\
&= \frac{(1+\beta_t)2-(1+\beta_t)(3-A_t-a_t^*)\beta_t - \beta_t[a_t^*+A_t-(2-A_t-a_t^*)\beta_t]}{(1-\theta\beta_t)\{[2-(3-A_t-a_t^*)\beta_t]\}^2} \\
&= \frac{(1+\beta_t)2-\beta_t[(1+\beta_t)(3-A_t-a_t^*)+a_t^*-A_t-(2-A_t-a_t^*)\beta_t]}{(1-\theta\beta_t)\{[2-(3-A_t-a_t^*)\beta_t]\}^2} \\
&= \frac{(1+\beta_t)2-\beta_t[(3-A_t-a_t^*)+\beta_t(3-A_t-a_t^*)+a_t^*-A_t-(2-A_t-a_t^*)\beta_t]}{(1-\theta\beta_t)\{[2-(3-A_t-a_t^*)\beta_t]\}^2} \\
&= \frac{(1+\beta_t)2-\beta_t[(3-A_t-a_t^*)+\beta_t+a_t^*-A_t]}{(1-\theta\beta_t)\{[2-(3-A_t-a_t^*)\beta_t]\}^2} \\
&= \frac{(1+\beta_t)2-\beta_t[3-2A_t+\beta_t]}{(1-\theta\beta_t)\{[2-(3-A_t-a_t^*)\beta_t]\}^2} \\
&= \frac{2-\beta_t+[2A_t-\beta_t]\beta_t}{(1-\theta\beta_t)\{[2-(3-A_t-a_t^*)\beta_t]\}^2}
\end{aligned}$$

Which is clear that $\frac{\partial\sigma_t^{\frac{S}{U}}}{\partial A_t}$ is a first order function of A_t and its second order $\frac{\partial\sigma_t^{\frac{S}{U}}}{\partial A_t\partial A_t}$ is positive. It is deduced that A_t can bring hump-shaped impact on between-group wage

income inequality $\sigma_t^{\frac{S}{U}}$. Further, since from (19): $A_t = \widetilde{A} - \phi\beta_t$, we know that $\frac{\partial A_t}{\beta_t} = -\phi$. Summarizing these findings conclude that the introduction of endogenous distribution of worker ability results in an inverted U-shaped impact of β_t on $\sigma_t^{\frac{S}{U}}$.

Next, consider the case that there is positive learning cost ($\eta > 0$) but no endogenous adjustment of worker ability ($\psi = 0$ & $\phi = 0$). In this case, only learning cost channel is in play. However, since the learning cost $\mu(w_t, \lambda_t, \beta_t)$ only appears in the threshold a_t^*, we can easily check the nonlinearity between $\sigma_t^{\frac{S}{U}}$ and learning cost $\mu(w_t, \lambda_t, \beta_t)$ by examining the first and second derivative of $\sigma_t^{\frac{S}{U}}$ to a_t^*. It is easily verified that the first derivative of $\sigma_t^{\frac{S}{U}}$ to a_t^* are identical to the first derivative of $\sigma_t^{\frac{S}{U}}$ to A_t:

$$\frac{\partial \sigma_t^{\frac{S}{U}}}{\partial a_t^*} = \frac{2 - \beta_t + [2A_t - \beta_t]\beta_t}{(1 - \theta\beta_t)\{[2 - (3 - A_t - a_t^*)\beta_t]\}^2} > 0$$

This result demonstrates that $\sigma_t^{\frac{S}{U}}$ increases in a_t^*. Then, combining this result with the finding in PROPOSITION 2 that $\frac{\partial a_t^*}{\partial \beta_t}$ has an inverted U-shaped relationship with β_t, we conclude that the relationship between β_t and $\sigma_t^{\frac{S}{U}}$ is also inverted U-shaped. It is noted that the way learning cost leading to hump-shaped responses of $\sigma_t^{\frac{S}{U}}$ replies totally on the mediating effect of the nonlinear relationship between β_t and a_t^*. In contrast, the way endogenous worker ability A_t leading to hump-shaped responses of $\sigma_t^{\frac{S}{U}}$ replies totally on the nonlinear relationship between A_t and $\sigma_t^{\frac{S}{U}}$ directly. This is why we test particularly the mediating effect empirically in section 2.

A.4 Proof of PROPOSITION 4

The proof follows the same strategy with the proof of PROPOSITION 3, thus the presentation is skipped.