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The Macroeconomics of Automation: Data, Theory, and Policy Analysis[1]

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Abstract

Advanced economies have experienced a significant drop in the fraction of the population employed in middle wage, "routine task-intensive" occupations. Applying machine learning techniques, we identify characteristics of those who used to be employed in such occupations and show they are now less likely to work in routine occupations. Instead, they are either not-participants in the labor force or working at occupations that tend to occupy the bottom of the wage distribution. We then develop a quantitative, heterogeneous agent, general equilibrium model of labor force participation, occupational choice, and capital investment. This allows us to quantify the role of advancement in automation technology in accounting for these labor market changes. We then use this framework as a laboratory to evaluate various public policies aimed at addressing the disappearance of routine employment and its consequent impacts on inequality.

Keywords: Polarization, Automation, Routine Employment, Labor Force Participation, Universal Basic Income, Unemployment Insurance, Retraining.

1. Introduction

Advances in automation technologies have left an indelible mark on the labor market of the U.S. and other industrialized economies over the past 40 years. An important literature demonstrates that these economies have experienced a significant drop in the fraction of the population employed in jobs in the middle of the occupational wage distribution (see, for instance, Autor, Katz and Kearney (2006), Goos and Manning (2007), Goos, Manning and Salomons (2009), Acemoglu and Autor (2011)). This hollowing out of the middle is linked to the decline of employment in *routine* occupations—those that focus on a limited set of tasks that can be performed by following a well-defined set of instructions and procedures. The routine nature of these tasks make them prime candidates to be performed by automation technologies (see Levy and Murnane (2003), and the subsequent literature).

This paper contributes to our understanding of this phenomenon along three dimensions. First, we apply machine learning techniques that allow us identify who are the workers with "routine occupational characteristics." With this chracterization in hand we track the labor market outcomes of the this *type* of individuals. Our key empirical findings is that the likelihood of this type of individuals to work in routine occupations has fallen significantly. Instead, they are now either not-participants in the labor force or working at occupations that tend to occupy the bottom of the wage distribution.

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What is causing this change in the likelihood to work in routine, middle-class, occupations? While there is ample research identifying technological change and automation as the primary factor, there could naturally be other complementary forces (see Section 2 for a discussion). Our second contribution is to quantify the specific role of automation. To do so, we develop in the second part of the paper a quantitive heterogeneous agent general equilibrium model of labor force participation, occupational choice, unemployment, and investment dynamics. We find that automation accounts for about half of the fall in the likelihood of working in routine occupations that we document for routine type individuals. Moreover, we use the model to study the aggregate and distributional effects of automation both in terms of allocations and welfare.

Given that we find an important quantitative role for automation, our third contribution is to use this new framework as a "laboratory" to evaluate various public policy proposals, where, given the general equilibrium emphasis of the model, each of the policies we consider must be financed through increased government distortionary taxation.

In what follows, we discuss each of these three parts in detail. In Section 2, we use data from the Current Population Survey (CPS) during the "pre-polarization" period of 1984-1989, to train a random forest algorithm to classify individuals in an agnostic manner. Individuals are classified into different categories based on their "occupational likelihood" having identified routine occupational characteristics. With this mapping we then track the evolution of individuals with such characteristics over time, and ask what has happened to the type of workers who would otherwise be employed in routine occupations during the "post-polarization" era. Are "routine-type" workers employed in different occupations now than they used to be? Do they tend to participate less in the labor force than they used to? Are they more often unemployed than they used to be?

Our key finding is that such individuals have experienced a fall of about 16% in the likelihood of working in routine occupations between the pre-polarization era and the post-polarization one. This decline in routine employment is necessarily accompanied by an offsetting increase in other labor market statuses; we find that instead of working in routine occupations about two-thirds of such individuals have ended up as non-participants in the labor force, with the remaining one-third of such individuals are employed in non-routine manual occupations (that tend to be at the bottom of the occupational wage distribution). Interestingly, we find the unemployment rates of such individuals to have remained roughly unchanged.

These finding guide the setup and calibration of a general equilibrium model which we present in Section 3. We have three goals in mind. First we use the model as a measurement device in order to quantify the specific role of automation in the fall in the likelihood of working in routine occupations for these individuals. Second, we use the model to asses the distributional effects of advanced automation. Third, we use the model to quantify the effects of various policy reforms. In what follows we briefly describe below the structure of the model.

Given our quantitative goal, we focus on a tangible measure of automation and its technological progress—specifically, information-and-communication-technology (ICT) capital that has been shown to capture various aggregate trends when embedded into a macroeconomic model (e.g., shares in overall investment and labor shares of national income; see Eden and Gaggl (2018). Firms invest optimally in capital, so that the degree of ICT adoption/automation is endogenous.

Since occupational employment is central to our analysis and empirical findings, we consider a model with three occupations: (i) non-routine cognitive (NRC), (ii) routine (R), and (iii) NRM, that represent high, middle, and low paying jobs, respectively.[2] The substitutability between ICT capital and R occupational labor is disciplined by the data. Any channel that affects firms optimal adoption of ICT capital affects the return to be working in a R occupation.

In the model, individuals with routine occupational characteristics (i.e. those who cannot work as NRC) vary in terms of their work ability in R and NRM occupations. Based on their abilities, workers optimally decide whether or not to participate in the labor force and, conditional on participating, sort into occupations. Labor force participants are either employed or unemployed due to search-and-matching frictions (Diamond (1982), Mortensen (1982) and Pissarides (1985 and). Given our interest in policy analysis, we introduce labor market frictions since certain interventions are targeted at the unemployed, while others affect the relative value of unemployment versus other labor market statuses. All government programs are financed with labor income and profit taxation.

We characterize the model equilibrium in Section 4 and discuss calibration and quantitative results in Section 5. In Section 6, the model is used as a laboratory to evaluate the aggregate and distributional effects of various policies. We consider two sets of policies where each is funded by distortionary taxation. First, we study the effect of an "occupational retraining" policy that is aimed at counteracting the effects of automation. The program is aimed at labor force non-participants, improving their ability in non-routine manual work. The policy induces workers back into the labor market, and improves their welfare. But this harms others: a displacement (or "crowding out") effect implies that newly trained workers compete with those who already selected into non-routine manual work, pushing down their wages, employment, and welfare.

The second set of policies are explicitly redistributive, transferring resources from high-wage workers (who, as the model shows, significantly benefit from automation) to middle- and low-wage workers. In these experiments, the unemployment margin plays a critical role. We consider: (i) increasing unemployment insurance benefits, (ii) introducing a universal basic income , and (iii) increasing transfers to labor force non-participants. While (i) is modestly successful in improving average welfare of all groups, policies (ii) and (iii) impose large welfare losses to high-wage workers and are very costly in terms of

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[2] See for instance, Autor, Katz and Kearney (2006), Goos and Manning (2007), and Jaimovich and Siu (2012).

aggregate income. We finally ask in our policy experiment whether there is another policy that can give rise to the large gains from redistribution without inducing large losses in output and welfare for the high-skilled? Our last exercise demonstrates that a (much) more progressive tax system, reducing the taxes on low-earners and balancing the budget by increasing the taxes on high-earners, can achieve much of the redistribution gains, but (i) without output losses, and with (ii) much smaller welfare losses for high income earners.

Finally, Section 7 concludes the paper, while the different Appendices discuss various robustness checks, both empirically and theoretically.

2. Employment and Occupation Trends

An important literature documents the changes in the task content of work, its relation to the decline in the cost of industrial robotics, computing, and information technology, and its implications for the structure of occupational employment and wages (see for example , Autor, Levy and Murnane (2003), Acemoglu and Autor (2011), Autor and Dorn (2013) and Atalay et al. (2018). Relatedly there is emerging literature that empirically asses the impact of automation on routine employment. For example, looking across countries, Michaels and Reenen (2014) find that the greater is the increase in ICT investment (at the industry-country level) the greater is the increase in the high-skilled labor share, and the greater is the decrease in the middle-skill share of labor income (and insignificant effects on the least-skilled group). Similarly, Acemoglu and Restrepo (2019) consider variation across US commuting zones and find find negative labor market effects given industry specific robotic penetration. Finally, Gaggl and Wright (2017) and Tuzel and Zhang (2019) use tax reforms in the U.K (the former) and the U.S. (the latter) that increase the incentives of ICT investment; both papers find that the increase in ICT reduce the number of workers who perform routine tasks while rewarding workers engaged in non-routine, cognitive-intensive task

In this section we add to this literature by pursuing the following goal. We aim to document what has happened to workers with "routine occupational characteristics" who would have been likely employed in routine occupations in the 1980s, a period we refer to as the "pre-polarization." Are these individuals employed now days in other occupations? Do they tend to be today more frequently unemployed? Or are they more likely to find themselves non-participants in the labor force? Findings these answers is challenging, because it involves a counterfactual experiment whereby we must decide which workers observed in the latter period of the data are those who would be routine occupational workers if they were observed in the earlier part of it.

To do this, we consider an empirical framework that classifies individuals according to their *likelihood* of employment in various occupational groups based on observed characteristics during the late 1980s. As such, we track the *type* of people who used to work in specific occupations (e.g. routine task-intensive ones) prior to or, at least, during an early phase of automation. We consider the employment and occupational choices of individuals classified by their “likely occupation”‘ over time, and track worker types with “routine occupational characteristics” as automation advances.

Before proceeding, it is useful to compare this to alternative approaches using panel data following specific individuals.[3] One could follow the evolution of the distribution of labor force and occupational choices of the 1980s cohort of routine workers. While this approach has natural appeal, it has two major disadvantages. First, such an exercise only follows a single cohort (or small number of cohorts) of individuals, and would be uninformative of the impact of automation on others cohorts, such as young workers entering the labor market at the turn of the 21st century. Second, the long-run labor market transitions of individuals over three decades confound macroeconomic effects with life-cycle effects—for example, the fact that individuals are more likely to get "promoted" to managerial occupations later in life, independent of advances in automation.

Our approach circumvents these issues. We do not attempt to track individuals who worked in a routine occupation over time. Instead, in *each year* we look for individuals with similar characteristics to those of routine workers in the late 1980s. By identifying these "likely routine" workers, we can analyze the labor market outcomes of the cross-section of such worker types over time, in a way that is not cohort-specific and does not confound life-cycle effects.

2.1 Where do workers in declining occupations go? A machine learning approach

We classify prime-aged individuals (25-64 years of age) from the CPS into types based on the occupation they would most likely have been employed in before the rise of automation. To obtain such a classification, we apply a random forest, machine learning (hereafter ML) algorithm using age, education, gender, and race as observable characteristics in a flexible manner. Unlike previous work, such as Cortes, Jaimovich and Siu (2017), the ML approach uses this information in a flexible and agnostic manner, that does not require us to pre-specify which characteristics, for e.g. which age groups are likely routine.

The occupational classification draws distinctions based on task intensity along two dimensions. The first is whether an occupation is routine or non-routine. The second is based on whether it is "cognitive" versus "manual" in task intensity. We thus end up with four categories of occupations: non-routine-cognitive (NRC); routine-cognitive (RC); non-routine-manual (NRM); and routine-manual (RM). Our occupation classification follows Jaimovich and Siu (2012 ; for more details about variable and sample definitions see Appendix A.1.1.

We use cross-sectional data on employed individuals using their current occupation, and unemployed individuals using their most recent occupation of employment. We do this

[3] Two candidate datasets are the 1979 National Longitudinal Survey of Youth (NLSY) and the Panel Study if Income Dynamics (PSID); for example, Cortes (2016) uses the PSID to study short-run occupation switching dynamics through the lens of labor market automation.

during the pre-polarization period (defined as 1984-1989) to train the ML algorithm to associate occupations to individual-level characteristics, where we pick 1989 as the benchmark year for comparisons, since per capita routine employment peaked that year (e.g. see Cortes, Jaimovich and Siu (2017)) We then apply the algorithm to assign persons to occupations in the remaining CPS subsamples. First, we use the predictions to assign the most "likely" occupation to labor force non-participants during the pre-polarization period. Second, we roll the predictions forward in time, 1990–2017, and predict occupations for all individuals. Doing so allows us to predict participation and occupational choices for all individuals had there been no changes in the economy.

2.2 Results

While our ML approach classifies individuals into four occupational groups, we present results here aggregating to two occupational types: *NRC* and *non-NRC* (i.e., RC, RM, and NRM). For the sake of exposition, we refer to these as *high-skill* and *low-skill* types, respectively.[4] The ML algorithm suggests that the strongest predictor for occupation choice in the late 1980s is a worker's educational attainment.[5]

Table 1 summarizes our findings. Columns (1) and (2) display the of the fraction of workers in—or their *propensity* to select into—labor force non-participation, unemployment, and employment in NRC, NRM and R occupations for low-skill men. In the late-1980s, the fraction of low-skill types employed in routine occupations was about 0.67; by 2017 this had dropped to approximately 0.57, a 10 percentage point (p.p.) or 16 log point fall.

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[4] We choose this delineation for substantive reasons as well: predictive power is high and classification errors are small at this level of aggregation, allowing for the minimization of noise in the type-specific series for employment and occupational choice (see Appendix A.1.2 for further discussion). Moreover, as documented in and Cortes (2016) and Cortes, Jaimovich and Siu (2017) , large differences in characteristics exist between high- and low-skill worker types, whereas routine (cogntive and manual; simply R hereafter) and NRM types are much more similar. This motivates previous theoretical analysis (such as the static, labor market models of and Autor, Katz and Kearney (2006) and Cortes, Jaimovich and Siu (2017)) as well as our modeling choice below.

[5] See Figure A1 in the Appendix, which displays a heat map of the probability of men in a specific education-age cell to be classified as high-skill. Lower educated men (with high-school diplomas or less) are always classified as low-skill, while those with more education (college graduates) are always classified as high-skill. For men with intermediate levels of education (some post-secondary), there is a gradient by age: younger men tend to sort to non-NRC occupations, older men toward NRC. Race (not shown in this picture) does not play an important role.

Table 1

Labor market status and occupation composition changes for men, 1989-2017 by type

	Low-skill		High-skill	
	(1)	(2)	(3)	(4)
	1989	2017	1989	2017
Population Weight	0.65	0.52	0.35	0.48
Fraction in R	0.67	0.57	0.02	0.06
Fraction in NRM	0.11	0.15	~0	0.01
Fraction in NRC	0.01	~0	0.99	0.90
Fraction in NLF	0.17	0.24	~0	0.03
Fraction in Unemployment	0.05	0.04	~0	0.01
Unemployment rate	0.06	0.06	~0	0.01

The decline in routine employment is necessarily accompanied by an offsetting increase in other labor market statuses. Where did these low-skill type men end up in 2017? As indicated by Table 2017, they did not go into high-wage NRC occupations, as the propensity to work in NRC remained essentially constant at zero.

By contrast, the probability of non-participation in the labor force (NLF) increased dramatically from 0.17 to 0.24, and the probability of employment in NRM occupations increased from about 0.11 to 0.15. These two propensity changes account for the entire fall in R employment. Roughly two-thirds of the decline can be accounted for by the increase in NLF, and the rest by the increase in NRM employment. This is a key result of our analysis: on average, low-skill types leaving R employment relocate into labor market statuses that are associated with lower income.[6] The bottom two rows of Table 1 indicate that the low-skill experienced no obvious change in the unemployment rate, or in their unemployment-to-population ratio.[7]

Are these increases in NLF and NRM propensity unique to the low-skilled or are these an economy-wide phenomena? Columns (3) and (4) of Table 1 summarize the changes in labor force and occupational employment statuses for high-skill men. This group has seen a decrease in NRC employment propensity (see Cortes, Jaimovich and Siu

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[6] Leaving the labor force is likely to be accompanied by increased dependency on transfer payments, while a transition to NRM is likely to be accompanied by a fall in wages and earnings (see, for instance, Autor and Dorn (2013)).

[7] Moreover, using high frequency CPS data we find that within each occupation, both the unemployment rate and exit rates show no low frequency trend over time. Unemployment exit rates were constructed from the outgoing rotation groups in the CPS and are calculated for three type of workers - Routine (R), Non-Routing Manual (NRM) and Non-Routine Cognitive (NRC) based on their last occupation prior to the unemployment spell.

(2018)) for analysis of the divergent gender trends in the high-skilled labor market.) But there is very little decline in labor force participation, no change in employment in NRM occupations, and a slight increase in R employment (see Beaudry, Green and Sand (2016) for a model with "crowding in" of high-skilled workers into middle-paying R occupations). This suggests that the changes for the low-skilled are particularly linked to the decline of R occupations.

High-skill women display similar patterns as those of high-skill men, but over a different time period. As is well known, the 1960-2000 period saw a pronounced increase in female labor force participation. But since the turn of the twenty-first century, this has plateaued and begun to fall even among the prime-aged. As such, the period since the turn of the century is more indicative of female occupational dynamics.

Columns 1 and 2 of Table 2 present the same information as in Table 1 but for low-skill women, 2001–2017. There has been a pronounced fall in the likelihood of employment in R occupations, with no increase in the propensity for NRC employment or unemployment.[8] Instead, they have seen offsetting increases in both the likelihood of non-participation and NRM employment; this split is again roughly two-thirds toward NLF, one-third toward NRM. This is the same split observed for low-skill men over the the 1989–2017 time period, and, as Columns 3 and 4 of Table 2 show, during 2001–2017 as well.

Table 2

Labor market status and occupation composition changes for non-NRC types

	Female		*Male*	
	(1)	(2)	(3)	(4)
	2001	2017	2001	2017
Population Weight	0.68	0.55	0.58	0.52
Fraction in R	0.39	0.30	0.64	0.57
Fraction in NRM	0.17	0.21	0.12	0.15
Fraction in NRC	0.07	0.06	0.01	~0
Fraction in NLF	0.34	0.40	0.19	0.24
Fraction in Unemployment	0.03	0.03	0.04	0.04
Unemployment rate	0.05	0.06	0.05	0.06

To summarize, the likelihood of working in R occupations has fallen for those individuals that were likely to be routine workers. This has been offset by increased likelihood of non-participation and NRM employment. In all cases considered, the offsetting labor market changes have been roughly split two-thirds toward non-participation, one-

[8] Though not displayed, these dynamics are not observed for high-skill women (as in the case of high-skill men).

third toward increased employment in low-wage, NRM occupations. We view accounting for these “stylized facts” to be important in our quantitative model analysis.

2.3 Using AFQT scores

A shortcoming of the ML approach is that it relies high-skill on workers’ observed educational attainment—a variable that is potentially endogenous to the automation forces under consideration. To address this, we consider a robustness check using respondent’s AFQT score as measured in the National Longitudinal Survey of Youth (NLSY). For comparability of scores between the 1979 and 1997 NLSY surveys, we use the standardized measure provided by Altonji, Bharadwaj and Lange (2012). The AFQT measure of cognitive ability is arguably a more direct, pre-labor market measure of a worker’s type, exogenous to automation and occupational choice. While the NLSY sample is too small to implement our ML approach, we use it to validate the patterns observed in the CPS.

Our analysis begins with the NLSY79, where we divide the sample into terciles of cognitive ability using the AFQT score and analyze the employment outcomes during 1989-1990.We drop the lowest decile of the AFQT distribution from the analysis, because men in this decile have an extremely low employment rate (below 60% around age 30). Given the discussion above regarding trends in female participation, we focus our analysis on men.

Table 3 indicates that, conditional on employment, there are large differences in the propensity to work in R or NRM occupations across AFQT scores. In the first tercile, 82% of workers were employed in a non-NRC occupation. While less formal, this simple approach classifies men with lower cognitive ability as “low skill.”

Table 3: Share of 1979 NLSY men working in Routine and non-Routine Manual occupations in 1989-1900

	Deciles		
	2-4	5-7	8-10
	(1)	(2)	(3)
Average share in NRM or R (non-NRC)	0.82	0.68	0.47

Notes: The table uses NLSY 1979, to report the share of workers in NRM or R (non-NRC) occupations by deciles of cognitive ability. For comparability of scores between the 1979 and 1997 NLSY surveys, we use the standardized measure provided by Altonji, Bharadwaj and Lange (2012)

Next, we ask where such workers end up in the post-polarization’ era. Table 4 compares the labor market status and occupational composition for the low-skilled between 1989-1990 (using the NLSY79) and 2012-2013 (using the NLSY97). The changes in participation and occupational choice for these men (of approximately 30 years of age) are consistent with the pattern from the ML approach using the CPS (for all prime working ages). There is a large decline in the likelihood of R employment (again of 16% as in the CPS analysis above), accompanied by increases in the likelihood of non-participation and NRM employment. The split between these two channels is roughly half-half. That there is greater movement into NRM in the NLSY is not surprising; this sample of low-skill men is younger than the CPS sample, and therefore displays greater labor force attachment (see Dorn et al.(2009) for discussion about the higher probability to leave routine employment for young workers).

Table 4: Labor market status and occupation composition changes for low cognitive ability men

	1989-1990	2012-2013
Fraction in R	0.600	0.502
Fraction in NRM	0.114	0.177
Fraction in NRC	0.157	0.134
Fraction in NLF	0.096	0.120
Fraction in Unemployment	0.033	0.060
Average age	29.35	29.69
Observations	437	553

Notes: The table uses NLSY 1979 and NLSY 1997, to report the fraction of workers in the second to fourth decile of cognitive ability in 5 labor market states in 1989-1990 and then again in 2012-2013: Employed in routine occupation (R); Employed in non-routine manual occupation (NRM); Employed in non-routine cognitive occupation (NRC); Not in the labor force (NLF); and unemployed.

To summarize, we view this exercise as complementary to the analysis of Section 2.2, indicating the quantitative importance of considering both, selection into labor force participation and occupational choice.

3. Model

As discussed above, the fall in the likelihood to work in routine, middle-class, occupations could be a result of various factors besides the rise of automation. In order to quantify the role of automation in this fall, we develop a quantitive general equilibirum model with participation and occupational choice. Our view is that the empirical analysis in Section 2 suggests that any model that studies the positive and normative effects of automation should incorporate these dimensions.

Motivated by the findings of Section 2.2 indicating a sharp distinction between NRC and non-NRC types, our model has two types of agents. We refer to these as high-skill (NRC) and low-skill (non-NRC) agents for simplicity. There are three distinct occupations: non-routine cognitive (NRC), routine (R), and non-routine manual (NRM).

Low-skill agents choose whether to participate in the labor market, and if they do, whether to seek employment in the R or NRM occupation. The low-skilled are heterogeneous, and each worker is endowed with two ability parameters (productivity draws)—one for occupation R and one for occupation NRM. Given their abilities in each occupation, individuals decide whether to participate in the labor force or not, and conditional on participation, in which occupation to search for employment. The occupational labor markets for low-skill workers are subject to a search and matching friction as in Diamond(1982), Mortensen(1982)and Pissarides (1985). Hence, the low sill occupation and participation choices depend on job finding probabilities and the equilibrium compensation in each job when employed. While Section 2.2 indicates no change in unemployment across the pre- and post-polarization eras, we model this labor market state since incentive effects on job search and vacancy creation come into consideration in the policy experiments we consider in Section 6.

Capital inputs in the forms of ICT capital and non-ICT capital are used in final production. Both capital stocks are owned by perfectly competitive final good producers who make investment decisions. Hence, the degree of automation in the form of ICT capital accumulation is endogenous (see Eden and Gaggl (2018) who document the rise of ICT capital in the last four decades).

For tractability, we assume that the high-skilled workers are identical, work only in the NRC occupation, and participate in a frictionless labor market. Moreover, again for tractability reasons, we assume that these workers are "capitalists" and own all firm equity in the economy; low-skilled workers are excluded from asset/credit markets and are "hand-to-mouth," with current consumption equal to current income.[9] This assumption regarding asset ownership, while simplistic, has empirical traction. For example, the Survey of Consumer Finances (SCF) reports median household net worth by the educational level

[9] Allowing all workers to hold assets introduces a number of technical complications. This includes the need to keep track of the marginal owner in firm's discount factor, the inclusion of wealth in low-skill workers' dynamic problems, and the need to track the distribution of firm ownership/capital holdings.

of household heads. Over the period of 1989-2016, median net worth of college graduates are more than 12 times as large as high school dropouts, and more than 4 times as large as high school graduates. Thus, highly educated individuals, who are empirically NRC worker types (as documented in Section 2.1), own the vast majority of assets in the US.

Finally, to allow for analysis of various government policies, we include the following taxes and transfers: a proportional tax on firms' profits, a proportional progressive tax on labor income, unemployment benefits, transfers to labor force non-participants, and (potentially) unconditional lump sum transfers.

Before formal presentation of the model, it is useful to comment on its relation to existing work. The basic production structure determining labor demand borrows from the static labor market models of Autor, Katz andKearney(2006)andCortes,JaimovichandSiu(2017) . Our analysis is most closely related to Eden and Gaggl (2018) and vom Lehn (2019 , who incorporate this labor demand framework into a dynamic, general equilibrium setting.

We build upon them taking key model elements but deviate in two important ways. First, Eden and Gaggl (2018) and vom Lehn (2019)and consider representative agent frameworks implying zero consumption and income inequality, making welfare implications of redistributive policies impossible to analyze. We consider a more empirically realistic distribution of income, with high-skilled individuals also being the owners of capital and firms, while low-skilled individuals earn labor income and receive government transfers. In addition, those papers do not model a labor force participation and unemployment margin. Labor supply is inelastic and the choice is along the "intensive" margin of which occupation to work in, not along the "extensive" margin of whether to work/seek work. By contrast, individuals in our model are not assumed to work, and may find themselves employed, unemployed, or out of the labor force. This is important for two reasons. First, the empirical analysis above suggested that labor force particiaption is the key margin of employment adjustment for the routine type workers. Second, allowing for labor force participation and unemployment is critical for the welfare analysis, if one is to consider the implications of policy changes, for instance, in transfer payments to labor force non-participants, unemployment insurance, or employment subsidies. Finally, in our framework all government insurance and redistribution programs (e.g., unemployment insurance, and recently discussed proposals for "universal basic income") must be financed through progressive labor and capital/profit taxation. This allows us to use the model as a laboratory for policy evaluation in Section 6.

3.1 Final Good Producers

Perfectly competitive, final good firms produce output (Y) using five inputs: intermediate goods (or service flows) produced from NRC, R, and NRM labor denoted Y_{NRC}, Y_{NRM}, and Y_R, respectively; and service flows from ICT capital (X_A) and non-ICT capital such as structures (K), which we refer to as simply "physical capital". The constant returns to scale production function for the final good is:

$$Y_t = Z_t K_t^{\gamma} \left((1-\eta) \left[(1-\alpha) Y_{NRC,t}^{\varsigma_1} + \alpha \left[X_A^{\nu} + Y_{R,t}^{\nu} \right]^{\frac{\varsigma_1}{\nu}} \right]^{\frac{\varsigma_2}{\varsigma_1}} + \eta Y_{NRM,t}^{\varsigma_2} \right)^{\frac{1-\gamma}{\varsigma_2}}$$

where Z_t denotes Hicks-neutral productivity, ν controls the elasticity of substitution between ICT capital and the R intermediate good, ς_1 controls the elasticity of substitution between the NRC intermediate good and the ICT-R composite, ς_2 which controls the elasticity of substitution between NRM and the composite of the previously discussed factors, and γ, η and α control the income shares to different factors of production.

Final good producers accumulate physical and ICT capital (which depreciate at rates δ_K and δ_A, respectively) and purchase the three intermediate goods from competitive markets at prevailing prices.[10] The relative price of investment in non-ICT is denoted $\phi_{K,t}$ and the relative price of ICT capital is $\phi_{A,t}$, where the final good is the numeraire ($P_Y = 1$). Hence, the firm's per-period profit is:

$$\pi = Y - P_R Y_R - P_{NRM} Y_{NRM} - P_{NRC} Y_{NRC} - \phi_A (X_A' - (1-\delta_A) X_A) - \phi_K (K' - (1-\delta_K) K)$$

with the prices of intermediate goods given by P_R, P_{NRC}, P_{NRM}. The firm's dynamic problem is:

$$V(K, X_A, \Lambda) = \max_{K', X_A', Y_R, Y_{NRM}, Y_{NRC}} \{(1 - T_\pi)\pi + \beta[V(K', X_A', \Lambda')]\}$$

where T_π is a tax rate on firms' profits, β is the discount factor, and $\Lambda = \{\phi_K, \phi_A, Z, T_\pi, P_R, P_{NRM}, P_{NRC}\}$ is a vector that contains all the state variables that the representative firm takes as given, which are either exogenously specified or determined in equilibrium.[11]

The firm accumulates physical and ICT capital in accordance with two standard Euler equations that equalize marginal cost and future return:

$$\phi_K = \beta[MPK' + (1-\delta_K)\phi_K']$$
$$\phi_A = \beta[MPA' + (1-\delta_A)\phi_A']$$

---

[10] The model is isomorphic if we assume that the final good firm also rents the capital from intermediate capital services producers.

[11] In writing the firm's problem this way we already impose consistency conditions such that the optimal choice is identical across firms and therefore represents the aggregate. As we show below, prices of intermediate goods are determined by the optimal demand and therefore by aggregate quantities of the intermediate goods. Moreover, since our analysis below is across steady states we already impose the stochastic discount factor being equal to β.

where MPK and MPA denote the marginal products of the two types of capital. Because profits are taxed net of investment costs, there are no equilibrium effects on optimal capital demand.[12]

3.2 Intermediate Goods Production

3.2.1 Routine Intermediate Good Producers

Intermediate good producers produce the routine intermediate good, Y_R (i.e., in the routine "occupation"), and sell it to the final good firm. In order to produce the routine intermediate good these producers recruit routine workers in a frictional labor market. As we discuss below, each low-skill agent is endowed with a pair of idiosyncratic productivity parameters, ϵ_R and ϵ_{NRM}, drawn from a joint distribution $\Gamma(\epsilon_R, \epsilon_{NRM})$; ϵ_R (ϵ_{NRM}) denotes the idiosyncratic ability of the worker if employed in production of the R (NRM) intermediate good. We assume that the labor markets for the low-skilled are frictional and fully segmented by good i and ability ϵ_i, for $i = \{R, NRM\}$. That is, there is full information about worker abilities allowing unemployed workers and vacancies to meet in occupation-*and-ability*-specific matches.

Hence, hiring low-skill workers with idiosyncratic ability ϵ_R (if these individuals endogenously decide to work in the R occupation in equilibrium) to produce routine intermediate goods requires a firm to post vacancies, v_{ϵ_R}, at flow cost of κ_{ϵ_R} per vacancy. A constant returns to scale matching function, $M\left(v_{\epsilon_R}, u_{\epsilon_R}\right)$, determines the number of new matches given vacancies and the number of unemployed job searchers (u_{ϵ_R}) in this good-ability-specific market. As is standard, firms take the tightness ratio, $\theta_{\epsilon_R} \equiv \frac{v_{\epsilon_R}}{u_{\epsilon_R}}$, and the vacancy filling probability $q\left(\theta_{R,\epsilon_R}\right)$ as given.

A matched firm and worker (with ability ϵ_R) produce $y_{\epsilon_R} = f_R \epsilon_R$ units of the R good, where f_R is taken parametrically. The productivity, f_R, is identical across all matches irrespective of ϵ_R. This intermediate good is sold to the final good producer at the competitive price P_R per unit. The firm pays a bargained wage ω_{R,ϵ_R} to the worker. Thus the flow profit from a match is $P_R f_R \epsilon_R - \omega_{R,\epsilon_R}$.

Let x_{ϵ_R} denote the number of employed R workers with idiosyncratic productivity ϵ_R. To derive the optimality condition for vacancy creation, we assume—for expositional clarity—that there exists a representative good-ability-specific firm that chooses v_{ϵ_R} to solve:

$$J\left(x_{\epsilon_R}, \Lambda\right) = \max_{v_{\epsilon_R}} \left\{(1 - T_\pi)\left[x_{\epsilon_R}\left(P_R f_R \epsilon_R - \omega_{\epsilon_R}\right) - \kappa_{\epsilon_R} v_{\epsilon_R}\right] + \beta\left[J\left(x'_{\epsilon_R}, \Lambda'\right)\right]\right\},$$

subject to the law of motion:

[12] For a similar approach see Abel (2007).

$$x'_{\epsilon_R} = (1-\delta)x_{\epsilon_R} + v_{\epsilon_R} q(\theta_{\epsilon_R}).$$

Here δ is the exogenous match separation probability (that is common across good-ability-specific matches). The first order condition implies the optimality condition for vacancy posting:[13]

$$\frac{\kappa_{\epsilon_R}}{q(\theta_{\epsilon_R})} = \beta\left[P_R f_R \epsilon_R - \omega_{\epsilon_R} + (1-\delta)\frac{\kappa_{\epsilon_R}}{q(\theta'_{\epsilon_R})}\right].$$

As with the case of capital taxation, because firm profits are taxed net of vacancy costs, there are no equilibrium effects of profit taxation on low-skilled job creation.

The quantity of efficiency-weighted labor input into the R occupation is then given by:

$$R = (1 - Pop_{NRC})\int_{\epsilon_R^*}^{\infty}\int_{-\infty}^{\epsilon_{NRM}(\epsilon_R)} E\,R_{\epsilon_R}\epsilon_R \Gamma'(\epsilon_R, \epsilon_{NRM})d\epsilon_{NRM}d\epsilon_R,$$

where Pop_{NRC} denotes the population share of high-skilled workers, and $ER_{\epsilon_R} = \frac{x_{\epsilon_R}}{(x_{\epsilon_R}+u_{\epsilon_R})}$ denotes the employment rate (per labor force participant) for a given ability level, ϵ_R. As we show in Section 4.2, the economy is characterized by an ability cutoff in the R and NRM occupational abilities as well as a function that determines in which occupation a worker works conditional on participating in the labor force. In Equation (4) the term ϵ_R^* denotes the cutoff ability in R such that all those with lesser ability do not work in R; the function $\epsilon_{NRM}(\epsilon_R)$ denotes the cutoff in ability NRM for each ϵ_R value such that below it, workers choose to work in R and not in NRM. Finally, $\Gamma'(\epsilon_R, \epsilon_{NRM})$ denotes the density function associated with the distribution function, Γ.

3.2.2 Non-Routine Manual Intermediate Good Producers

The labor market for the NRM occupation is identical in structure to the R occupation and obeys the same optimality principles. We do not repeat the exposition for brevity, and simply present the vacancy posting optimality condition:

$$\frac{\kappa_{\epsilon_{NRM}}}{q(\theta_{\epsilon_{NRM}})} = \beta\left[P_{NRM} f_{NRM} \epsilon_{NRM} - \omega_{\epsilon_{NRM}} + (1-\delta)\frac{\kappa_{\epsilon_{NRM}}}{q(\theta'_{\epsilon_{NRM}})}\right].$$

13

The use of a representative firm is for convenience only. An identical optimal condition can be derived when assuming a Bellman value for an open vacancy, a Bellman value for a filled job, and a zero profit condition:

$$\begin{aligned} V_{R,\epsilon_R} &= -(1-T_\pi)\kappa_{R,\epsilon_R} + q(\theta_{R,\epsilon_R})E[\Theta J'_{R,\epsilon_R}] = 0, \\ J_{R,\epsilon_R} &= (1-T_\pi)[f_R \epsilon_R P_R - \omega_{R,\epsilon_R}] + (1-\delta)E[\Theta J'_{R,\epsilon_R}]. \end{aligned}$$

In equilibrum, the quantity of efficiency-weighted non-routine-manual labor input is given by:

$$NRM = (1 - Pop_{NRC}) \int_{\epsilon_{NRM}^*}^{\infty} \int_{-\infty}^{\epsilon_R(\epsilon_{NRM})} E\, R_{\epsilon_{NRM}} \epsilon_{NRM} \Gamma'(\epsilon_R, \epsilon_{NRM}) d\epsilon_R d\epsilon_{NRM},$$

where $ER_{\epsilon_{NRM}} = \frac{x_{\epsilon_{NRM}}}{(x_{\epsilon_{NRM}} + u_{\epsilon_{NRM}})}$.

3.2.3 Non-Routine Cognitive Intermediate Good Producers

Given our primary interest is in the low-skilled labor market, we assume for simplicity that the high-skilled labor market has no matching frictions. High-skill workers make no occupational choice, work only in NRC production, and are identical in ability (normalized to unity). The problem of the NRC intermediate good producer is static:

$$\max_{x_{NRC}} f_{NRC} P_{NRC} x_{NRC} - \omega_{NRC} x_{NRC},$$

taking productivity, f_{NRC}, and competitively determined prices, P_{NRC} and ω_{NRC} as given. This gives rise to the simple marginal revenue product equals wage condition in equilibrium:

$$\omega_{NRC} = f_{NRC} P_{NRC}.$$

3.3 Workers

In this subsection, we describe the dynamic optimization problem of high-skill and low-skill workers. All workers are infinitely-lived and discount the future at rate $0 < \beta < 1$.

3.3.1 Non-Routine Cognitive Workers

The results of Section 2.1 indicate that the high-skilled experience essentially zero unemployment that hasn't changed over time. Given this, we abstract from search-and-matching frictions. Our ultimate interest is in accounting for general equilibrium effects of various policy proposals, that must be financed through (progressive) distortionary income taxation. Given this, we opt to capture these distortions in the simplest way; specifically, we model a 'labor supply margin' of hours worked choice by the high-skilled that responds to variation in the distortionary tax rate.

Formally, an exogenously specified fraction of workers are high-skill (NRC) workers, who have preferences over consumption, C_{NRC} denoted by the utility $U(C_{NRC})$, and derive disutility from hours spent working, L_{NRC} denoted by $G(L_{NRC})$.[14] They earn ω_{NRC} per hour worked and are taxed on labor income at the rate T_{NRC}. High-skill workers save in the form of an asset that represents claims to profits of intermediate goods firms. Let B_{NRC} denote

---

[14] For exposition clarity we assume separability in consumption and leisure as we assume this formulation in our quantitive work.

the beginning of period value of such claims (the sum of dividends and resale value) that are traded at price p. Then, NRC workers solve:

$$V_{NRC}(B_{NRC},\Lambda)=\max_{C_{NRC},B'}\{U(C_{NRC})-G(L_{NRC})+\beta[V_{NRC}(B'_{NRC},\Lambda')]\}$$
$$\text{s.t.: } C_{NRC}+pB'_{NRC}=L_{NRC}\omega_{NRC}(1-T_{NRC})+pB_{NRC}$$

3.3.2 Routine and Non-Routine Manual Workers

Let $\epsilon=(\epsilon_R,\epsilon_{NRM})$ denote a worker's (constant) idiosyncratic ability draw. Given ϵ, an unmatched low-skill worker simultaneously chooses whether to participate in the labor market or not and, conditional on participating, in which occupational labor market to search. Let $V_{e,\epsilon_R}(\Lambda)$ denote the value of being an employed R worker, $V_{u,\epsilon_R}(\Lambda)$ the value of being an unemployed R worker, $V_{e,\epsilon_{NRM}}(\Lambda)$ the value of being an employed NRM worker, and $V_{u,\epsilon_{NRM}}(\Lambda)$ the value of being an unemployed NRM worker. Let the value of labor force non-participation be $V_{\epsilon_O}(\Lambda)$. As before, Λ denotes the collection of aggregate state variables that workers take parametrically.

The value of being employed as an R worker is given by:

$$\begin{aligned}V_{e,\epsilon_R}(\Lambda) \;=\;\; & U\big(C_{e,\epsilon_R}\big)+\beta\delta\big[\max\big\{V_{u,\epsilon_R}(\Lambda'),V_{u,\epsilon_{NRM}}(\Lambda'),V_{\epsilon_O}(\Lambda')\big\}\big]+\\ & \beta(1-\delta)\big[\max\big\{V_{e,\epsilon_R}(\Lambda'),V_{u,\epsilon_R}(\Lambda'),V_{u,\epsilon_{NRM}}(\Lambda'),V_{\epsilon_O}(\Lambda')\big\}\big].\end{aligned}$$

Current period consumption, C_{e,ϵ_R}, must satisfy the budget constraint:

$$C_{e,\epsilon_R}=\omega_{\epsilon_R}\big(1-T_{\epsilon_R}\big),$$

where ω_{ϵ_R} denotes the wage (low-skill workers supply one unit of labor inelastically when employed), and T_{ϵ_R} is the income tax rate.

Routine matches separate with exogenous probability δ. If the match separates, the worker chooses whether to leave or remain in the labor force in the following period; in the latter case, the worker also chooses whether to search for employment in the R or NRM occupation. If the match does not separate, the worker has the choice of remaining matched in the following period, leaving to unemployment, or leaving the labor force.[15]

An unemployed worker searching for a match in the R occupation meets a vacancy with probability $\mu\big(\theta_{\epsilon_R}\big)$. Upon meeting, the worker a chooses whether to match and become employed, remain unmatched/unemployed, or leave the labor force. The dynamic problem of an unemployed worker is:

---

[15] Given our interest in steady state comparison, an employed worker will never switch from employment in one other sector to another.

$$V_{u,\epsilon_R}(,\Lambda) \;=\; U\left(C_{u,\epsilon_R}\right) + \beta\left(1-\mu\left(\theta_{\epsilon_R}\right)\right)\left[\max\left\{V_{u,\epsilon_R}(\Lambda'), V_{u,\epsilon_{NRM}}(\Lambda'), V_{\epsilon_O}(\Lambda')\right\}\right] + \beta\mu\left(\theta_{\epsilon_R}\right)\left[\max\left\{V_{e,\epsilon_R}(\Lambda'), V_{u,\epsilon_R}(\Lambda'), V_{u,\epsilon_{NRM}}(\Lambda'), V_{\epsilon_O}(\Lambda')\right\}\right],$$

subject to:

$$C_{u,\epsilon_R} = b\omega_{\epsilon_R},$$

where b denotes the (net of tax) unemployment insurance replacement rate for a worker with R ability, ϵ_R. The problem for workers who are employed in, or unemployed and choose to search in, the NRM occupation is identical in structure to that just described, except with R-subscripts replaced by NRM-subscripts and vice versa.

A worker who is out of the labor force chooses whether to remain a non-participant, or become unemployed in either R or NRM. We assume that the transfer to labor force non-participants is constant and independent of ability. Hence, the dynamic problem is:

$$V_{\epsilon_O}(\Lambda) \;=\; U\left(C_{\quad O}\right) + \beta\left[\max\left\{V_{u,\epsilon_R}(\Lambda'), V_{u,\epsilon_{NRM}}(\Lambda'), V_{\epsilon_O}(\Lambda')\right\}\right],$$

subject to:

$$C_{\quad O} = b_O.$$

Here, b_O denotes (net of tax) government transfers to non-participants. Although non-participants receive the same income, they have different abilities, ϵ, and face differing likelihoods of labor force participation following a change in the economy.

3.4 Wage Bargaining

A match between an intermediate good firm and a worker generates a positive surplus that must be split. As is common in the literature, we assume the Nash bargaining solution to surplus division. We present the Nash bargaining problem for an R match; the exposition for an NRM match is analogous.

The surplus for a firm is the marginal value of employing an additional worker:

$$\frac{\partial J\left(x_{\epsilon_R}, \Lambda\right)}{\partial x_{\epsilon_R}} = (1-T_\pi)\left(f_R\epsilon_R P_R - \omega_{\epsilon_R}\right) + (1-\delta)\beta\left[\frac{\partial J\left(x'_{\epsilon_R}, \Lambda'\right)}{\partial x'_{\epsilon_R}}\right].$$

The surplus for an employed worker with idiosyncratic ability ϵ_R is:

$$\widetilde{V}_{\epsilon_R}(\Lambda) = V_{e,R,\epsilon}(\Lambda) - \max\left\{V_{u,\epsilon_R}(\Lambda), V_{u,\epsilon_{NRM}}(\Lambda), V_{\epsilon_O}(\Lambda)\right\}.$$

The worker's outside option is the optimal choice across searching for a new match in either the R or NRM occupation, or labor force non-participation.

Denoting the worker's bargaining weight by τ and the firm's by $1-\tau$, the wage for a worker employed in R with ability ϵ_R is the solution to:

$$\max_{\omega_{\epsilon_R}}[\widetilde{V}_{\epsilon_R}(\Lambda)]^{\tau}[\frac{\partial J(x_{\epsilon_R},\Lambda)}{\partial x_{\epsilon_R}}]^{1-\tau}.$$

In Section 4 we impose functional form assumptions that allow for an analytic solution for the resulting wage function.

3.5 Government Budget Constraint

Total unemployment insurance transfers to low-skill workers searching for NRM employment is given by:

$$UI_{NRM} = (1 - Pop_{NRC})\int_{\epsilon_{NRM}^*}^{\infty}\int_{-\infty}^{\epsilon_R(\epsilon_{NRM})} U\,R_{\epsilon_{NRM}} b\omega_{\epsilon_{NRM}}\Gamma'(\epsilon_R,\epsilon_{NRM})d\epsilon_R d\epsilon_{NRM},$$

where $UR_{\epsilon_{NRM}} = 1 - ER_{\epsilon_{NRM}} = \frac{u_{\epsilon_{NRM}}}{(x_{\epsilon_{NRM}}+u_{\epsilon_{NRM}})}$ is the unemployment rate at ability level ϵ_{NRM}. Similarly, transfers to unemployed R workers is:

$$UI_R = (1 - Pop_{NRC})\int_{\epsilon_R^*}^{\infty}\int_{-\infty}^{\epsilon_{NRM}(\epsilon_R)} U\,R_{\epsilon_{NRM}} b\omega_{\epsilon_R}\Gamma'(\epsilon_R,\epsilon_{NRM})d\epsilon_{NRM} d\epsilon_R,$$

where $UR_{\epsilon_R} = 1 - ER_{\epsilon_R} = \frac{u_{\epsilon_R}}{(x_{\epsilon_R}+u_{\epsilon_R})}$. Letting NLF denote the measure of low-skill workers outside the labor force:

$$NLF = \int_{-\infty}^{\epsilon_R^*}\int_{-\infty}^{\epsilon_{NRM}^*}\Gamma'(\epsilon_R,\epsilon_{NRM})d\epsilon_{NRM}d\epsilon_R,$$

total government transfers to this group is $NLFb_o$.

Government revenues are derived from labor and profit taxation. Labor taxes collected from employed NRM and R workers is given by:

$$Rev_{NRM} = (1 - Pop_{NRC})\int_{\epsilon_{NRM}^*}^{\infty}\int_{-\infty}^{\epsilon_R(\epsilon_{NRM})} E\,R_{\epsilon_{NRM}} T_{\epsilon_{NRM}}\omega_{\epsilon_{NRM}}\Gamma'(\epsilon_R,\epsilon_{NRM})d\epsilon_R d\epsilon_{NRM},$$

and :

$$Rev_R = (1 - Pop_{NRC})\int_{\epsilon_R^*}^{\infty}\int_{-\infty}^{\epsilon_{NRM}(\epsilon_R)} E\,R_{\epsilon_R} T_{\epsilon_R}\omega_{\epsilon_R}\Gamma'(\epsilon_R,\epsilon_{NRM})d\epsilon_{NRM} d\epsilon_R,$$

respectively. Labor taxes collected from NRC workers is:

$$Rev_{NRC} = Pop_{NRC}L_{NRC}\omega_{NRC}T_{NRC}.$$

Revenue from the tax on profits of intermediate producers in the NRM and R occupations is given by:

$$Rev_{\pi_{NRM}} = (T_\pi)(1 - Pop_{NRC}) \int_{\epsilon_{NRM}^*}^{\infty} \int_{-\infty}^{\epsilon_R(\epsilon_{NRM})} \left[x_{\epsilon_{NRM}}\left(f_{\epsilon_{NRM}}\epsilon_{\epsilon_{NRM}}P_{NRM} - \omega_{\epsilon_{NRM}}\right) - \kappa_{\epsilon_{NRM}}v_{\epsilon_{NRM}}\right] \Gamma'(\epsilon_R, \epsilon_{NRM}) d\epsilon_R d\epsilon_{NRM},$$

$$Rev_{\pi_R} = (T_\pi)(1 - Pop_{NRC}) \int_{\epsilon_R^*}^{\infty} \int_{-\infty}^{\epsilon_{NRM}(\epsilon_R)} \left[x_{\epsilon_R}\left(f_R\epsilon_R P_R - \omega_{\epsilon_R}\right) - \kappa_{\epsilon_R}v_{\epsilon_R}\right] \Gamma'(\epsilon_R, \epsilon_{NRM}) d\epsilon_{NRM} d\epsilon_R.$$

Tax revenue from the final good producer is given by:

$$Rev_\pi = T_\pi[Y - P_R Y_R - P_{NRM}Y_{NRM} - P_{NRC}Y_{NRC} - \phi_A(X_A' - (1-\delta_A)X_A) - \phi_K(K' - (1-\delta_K)K)].$$

The government does not borrow or save, so that at each point in time the following budget constraint holds:

$$NLFb_o + UI_{NRM} + UI_R = Rev_{NRC} + Rev_R + Rev_{NRM} + Rev_\pi + Rev_{\pi_R} + Rev_{\pi_{NRM}}.$$

3.6 Equilibrium

To summarize the structure of the model, an exogenously specified fraction of workers are high-skilled. They supply their labor in a frictionless labor market to producing the NRC intermediate good, and receive a market wage equal to their marginal revenue product.

With respect to low skilled individuals, each low-skill agent is endowed with a pair of idiosyncratic productivity parameters, ϵ_R and ϵ_{NRM}, drawn from a joint distribution $\Gamma(\epsilon_R, \epsilon_{NRM})$. The labor markets for the low-skilled are frictional and fully segmented by good i and ability ϵ_i, for $i = \{R, NRM\}$.

Unemployed low-skill workers choose whether to search in the R or NRM labor market or to leave the labor force. Low-skill workers work for profit-maximizing intermediate producers. Producers decide whether to maintain vacancies and, if so, in which good-and-ability specific market. Given equilibrium prices, outside options, and government policies, intermediate good firms choose vacancies optimally. Free entry implies zero lifetime profits.

Hence, formally, given productivities, $\{Z, \phi_K, \phi_A\, f_R, f_{NRM}, f_{NRC}\}$, the distribution of low-skill abilities, $\Gamma(\epsilon_R, \epsilon_{NRM})$, and the population fraction of high-skill workers, Pop_{NRC}, a symmetric stationary equilibrium with Nash bargaining is a collection of:

- intermediate good prices, $\{P_{NRC}, P_R, P_{NRM}\}$, and prices on equity claims $\{p\}$;
- wages $\{\omega_{NRC}\}$ and $\{\omega_{\epsilon_R}, \omega_{\epsilon_{NRM}}\}$ for all $\epsilon_R, \epsilon_{NRM}$;
- tightness ratios, $\{\theta_{\epsilon_R}, \theta_{\epsilon_{NRM}}\}$, and vacancies, $\{v_{\epsilon_R}, v_{\epsilon_{NRM}}\}$, for all $\epsilon_R, \epsilon_{NRM}$;

- worker quantities, $\{C_{NRC}, X_{NRC}, B_{NRC}, C_o\}$ and $\{C_{e,\epsilon_R}, C_{u,\epsilon_R}, C_{e,\epsilon_{NRM}}, C_{u,\epsilon_{NRM}}\}$ for all $\epsilon_R, \epsilon_{NRM}$;
- labor input, x_{NRC} and $\{x_{\epsilon_R}, x_{\epsilon_{NRM}}\}$ for all $\epsilon_R, \epsilon_{NRM}$;
- firm quantities, $\{Y, Y_{NRC}, Y_R, Y_{NRM}, K, X_A\}$; and
- policy, $\{T_\pi, T_{NRC}, b, b_o\}$ and $\{T_{\epsilon_R}, T_{\epsilon_{NRM}}\}$ for all $\epsilon_R, \epsilon_{NRM}$

such that

- final good and intermediate good firms are maximizing (and in particular, physical capital accumulation, automation capital accumulation, and vacancy creation is optimal),
- workers are maximizing (specifically, high-skill workers are making saving and labor supply decisions, and low-skill workers are making participation and occupational choices optimally),
- R and NRM wages solve their respective Nash bargaining problems,
- the final good market clears:

$$\begin{aligned} Y = Pop_{NRC}C_{NRC} \quad & +(1 - Pop_{NRC})\Big[\int_{\epsilon_R^*}^{\infty}\int_{-\infty}^{\epsilon_{NRM}(\epsilon_R)} (ER_{\epsilon_R}C_{e,\epsilon_R} + UR_{\epsilon_R}C_{u,\epsilon_R} + \kappa_{\epsilon_R}v_{\epsilon_R})\Gamma'(\epsilon_R, \epsilon_{NRM})d\epsilon_{NRM}d\epsilon_R \\ & + \int_{\epsilon_{NRM}^*}^{\infty}\int_{-\infty}^{\epsilon_R(\epsilon_{NRM})} (ER_{\epsilon_{NRM}}C_{e,\epsilon_{NRM}} + UR_{\epsilon_{NRM}}C_{u,\epsilon_{NRM}} + \kappa_{\epsilon_{NRM}}v_{\epsilon_{NRM}})\Gamma'(\epsilon_R, \epsilon_{NRM})d\epsilon_R d\epsilon_{NRM} \\ & + \int_{-\infty}^{\epsilon_R^*}\int_{-\infty}^{\epsilon_{NRM}^*} C_o\,\Gamma'(\epsilon_R, \epsilon_{NRM})d\epsilon_{NRM}d\epsilon_R\Big] + \phi_A(X_A' - (1 - \delta_A)X_A) + \phi_K(K' - (1 - \delta_K)K) \end{aligned}$$

- intermediate good markets clear:

$$\begin{aligned} Y_{NRC} &= f_{NRC}x_{NRC} = f_{NRC}H_{NRC}Pop_{NRC}, \\ Y_R &= f_R R,\ Y_{NRM} = f_{NRM}NRM \end{aligned}$$

- the equity market clears: $B = 1$, and
- the government's budget constraint is satisfied.

4. Construction of Steady State Equilibrium

In this section we characterize the steady state equilibrium. We highlight a set of sufficient assumptions that deliver, as in the data, unemployment rates that do not vary as ICT price fall. The three conditions are: (i) a constant relative risk aversion (hereafter CRRA) function, $U(.)$, (ii) vacancy costs, $\kappa_{\epsilon_R}, \kappa_{\epsilon_{NRM}}$ for all $\epsilon_R, \epsilon_{NRM}$, that are proportional to productivity, and (iii) income for low-skill labor force participants that is proportional to their wage (i.e., unemployment benefits specified as a replacement rate relative to the wage when employed).

4.1 Wages and Tightness Ratios

Recall the bargaining problem characterizing the R occupation, equation (5) As we show in Appendix A.2.1, the resulting wage for an R worker with ability ϵ_R is:

$$\omega_{\epsilon_R} = f_R \epsilon_R P_R - \frac{1-\tau}{\tau} \frac{U\left(C_{e,\epsilon_R}\right) - U\left(C_{u,\epsilon_R}\right)}{U'\left(C_{e,\epsilon_R}\right)\left(1 - T_{\epsilon_R}\right) - U'\left(C_{u,\epsilon_R}\right) b} + \theta_{\epsilon_R} \kappa_{\epsilon_R}$$

This is an increasing function of the worker's marginal revenue product, $f_R \epsilon_R P_R$, as well as labor market tightness, θ_{ϵ_R}, which reflects the outside option for the worker. Unlike the standard DMP model with risk neutrality, the wage is also affected by the utility and marginal utility differences between employed and unemployed workers.

With an eye toward quantitative analysis, we assume a CRRA utility function, $U(C) = \frac{C^{1-\sigma}}{1-\sigma}$. We show in Appendix A.2.1 that the wage function simplifies to:

$$\omega_{\epsilon_R} = \frac{1}{1+\Psi} \left[f_R \epsilon_R P_R + \theta_{R,\epsilon_R} \kappa_{R,\epsilon_R} \right],$$

where $\Psi = \frac{(1-\tau)}{\tau(1-\sigma)}$. By following Pissarides (2000) and assuming that the hiring cost, κ_{ϵ_R}, is proportional to the worker's ability (reflecting the idea that it is more costly to hire more productive workers):

$$\kappa_{\epsilon_R} = f_R P_R \epsilon_R \kappa_0,$$

where $\kappa_0 > 0$ is an exogenous parameter it then follows that the wage function (7) is linear in worker ability, ϵ_R. With these assumptions, we show in Appendix A.2.1 that the equilibrium tightness ratio implicitly solves:

$$\left[\frac{1 - \beta(1-\delta)}{q\left(\theta_{\epsilon_R}\right)} + \beta \frac{\theta_{\epsilon_R}}{1+\Psi} \right] \kappa_0 = \beta \frac{\Psi}{1+\Psi}, \quad \forall \epsilon_R.$$

Hence, equilibrium tightness ratio is independent of productivities, $\{Z, \phi_K, \phi_A, f_R, f_{NRM}, f_{NRC}\}$. The same is true of tightness in NRM as well. The model yields a constant tightness ratio for each occupation in steady state, even as productivity (i.e. automation technology) changes. This makes the model consistent with the empirical patterns of the unemployment rate discussed in Section 2.

4.2 Productivity Cutoffs

As indicated by (8), equilibrium tightness is also independent of worker ability. This is useful in establishing results regarding productivity cutoffs. In Appendix A.3 we show that the steady state values of unemployment can be expressed as:

$$
\begin{aligned}
V_{u,\epsilon_R} &= \frac{(f_R\ P_R \epsilon_R)^{1-\sigma}}{1-\beta} \daleth_R(\epsilon_R),\\
V_{u,\epsilon_{NRM}} &= \frac{(f_{NRM} P_{NRM} \epsilon_{NRM})^{1-\sigma}}{1-\beta} \daleth_{NRM}(\epsilon_{NRM}),
\end{aligned}
$$

for all $\epsilon_R, \epsilon_{NRM}$. Here, $\daleth_R(\epsilon_R)$ and $\daleth_{NRM}(\epsilon_{NRM})$ are functions of exogenous parameters and occupation-and-ability specific tightness ratios:

$$
\begin{aligned}
\daleth_R(\epsilon_R) &= \frac{\left(b\dfrac{1+\theta_{\epsilon_R}\kappa_0}{1+\Psi}\right)^{1-\sigma}}{1-\sigma} + \left(\frac{1+\theta_{\epsilon_R}\kappa_0}{1+\Psi}\right)^{-\sigma}\left[\left(1-T_{\epsilon_R}\right)^{1-\sigma} - b^{1-\sigma}\right]\theta_{\epsilon_R}\frac{\tau}{1-\tau}\kappa_0,\\
\daleth_{NRM}(\epsilon_{NRM}) &= \frac{\left(b\dfrac{1+\theta_{\epsilon_{NRM}}\kappa_0}{1+\Psi}\right)^{1-\sigma}}{1-\sigma} + \left(\frac{1+\theta_{\epsilon_{NRM}}\kappa_0}{1+\Psi}\right)^{-\sigma}\left[\left(1-T_{\epsilon_{NRM}}\right)^{1-\sigma} - b^{1-\sigma}\right]\theta_{\epsilon_{NRM}}\frac{\tau}{1-\tau}\kappa_0.
\end{aligned}
$$

We have assumed that the unemployment insurance replacement rate, b, is constant across low-skill worker abilities. Equation (8) indicates that labor market tightness ratios are constant across abilities: $\theta_{\epsilon_R} = \theta_R$, $\forall \epsilon_R$, and $\theta_{\epsilon_{NRM}} = \theta_{NRM}$, $\forall \epsilon_{NRM}$. If we assume that low-skill tax rates are independent of ability, $T_{\epsilon_R} = T_R$, $\forall \epsilon_R$, and $T_{\epsilon_{NRM}} = T_{NRM}$, $\forall \epsilon_{NRM}$, this implies that $\daleth_R(\epsilon_R) = \daleth_R$ and $\daleth_{NRM}(\epsilon_{NRM}) = \daleth_{NRM}$ are constant across worker abilities.

This allows us to establish the following results. Recall that transfers to labor force non-participants is independent of ability; hence the value of non-participation is independent of ability. Therefore, we can solve for cutoff values ϵ_R^* and ϵ_{NRM}^* such that a worker with ability $\epsilon = (\epsilon_R, \epsilon_{NRM})$ below both cutoffs prefers labor force non-participation. These cutoffs are given by:

$$
\begin{aligned}
\epsilon_R^* &= \frac{b_o}{f_R P_R}\left(\frac{1}{\daleth_R}\right)^{\frac{1}{1-\sigma}},\\
\epsilon_{NRM}^* &= \frac{1}{f_{NRM} P_{NRM}}\left(\frac{b_o}{\daleth_{NRM}}\right)^{\frac{1}{1-\sigma}}.
\end{aligned}
$$

Those who draw ϵ above either cutoff (or both) choose to participate in the labor market. Which occupation the worker searches in is determined by the values of unemployment, V_{u,ϵ_R} and $V_{u,\epsilon_{NRM}}$. Specifically, for each $\epsilon_R (> \epsilon_R^*)$ there exists an $\hat{\epsilon}_{NRM}$ such that for $\epsilon_{NRM} < \hat{\epsilon}_{NRM}$, the worker chooses unemployment in R, and for $\epsilon_{NRM} \geq \hat{\epsilon}_{NRM}$ the worker searches in NRM. This cutoff is the solution to:

$$\frac{(f_R P_R \epsilon_R)^{1-\sigma}}{1-\beta} \daleth_R = \frac{(f_{NRM} P_{NRM} \epsilon_{NRM})^{1-\sigma}}{1-\beta} \daleth_{NRM},$$

implying a linear function of the form:

$$\hat{\epsilon}_{NRM}\,(\epsilon_R) = \left(\frac{\daleth_R}{\daleth_{NRM}}\right)^{\frac{1}{1-\sigma}} \frac{f_R P_R}{f_{NRM} P_{NRM}} \epsilon_R.$$

This result is important from a computational perspective since it implies that the bounds of the various integrals in the model are linear. That together with tightness ratios being constant implies that we can solve for the equilibrium allocations and perform welfare calculations exploiting these closed form results, even though the model features curvature in utility, production, and frictions in the labor market.

5. Quantitative Results

In this section we calibrate the model economy and evaluate the impact of advancement in automation technology. We model this as a fall in the relative price of ICT capital, ϕ_A (or equivalently, an increase in the productivity in transforming final goods into ICT capital, $1/\phi_A$). As a guide, we target pre-automation moments, feed in the observed change in the price of automation, and evaluate model performance by comparing 2017 predictions to observed US data.

5.1 Calibration

We begin this section by discussing the parametrization of the model. Table 5 lists the various parameters and their values.

Table 5

Calibration

Parameter	**Value**	**Target**
Ability Distribution		
μ_{NRM}	1	
μ_R	1	Normalization
σ_{NRM}	0.9803	
σ_R	0.7436	Occupations allocations variance of observed wages
$\rho_{R,NRM}$	0	See text for details
Preferences		
β	0.9957	Monthly frequency; $r_{annual} = 0.05$
σ	1	log utility
Labor Market Frictions		

δ	0.02	Monthly exit rate 1989
elasticity of matches to v	0.5	Pissarides and Petrongolo (2001)
Taxes and Transfers		
b	0.5	Maximum allowed, US 1989
b_o	.0813	Marginal worker indifferent between NLF and unemployment
T_{NRM}	0.137	
T_R	0.137	Average group tax rate
T_{NRC}	0.267	
Depreciation Rates		
δ_K	0.06	Annual depreciation rates (see Eden and Gaggl (2018))
δ_A	0.19	
Prices of Capital		
ϕ_K	1	
ϕ_A	0.77	Eden and Gaggl (2018)
$\frac{\phi_A^{2017}}{\phi_A^{1989}}$	0.3244	Fall in ICT prices 1989-2017 (see Eden and Gaggl (2018))
Production Function: Shares		
η	.1099	
α	0.8154	Labor share, Routine Labor Share, ICT capital Income share, 198
f_R	0.3022	
Production Function: Elasticities		
γ	0.31	Physical capital income share (see Eden and Gaggl (2018))
ς_2	0	≈constant NRM income share
ν	0.46	
ς_1	-1.1	Split of R workers between NLF and NRM and Δ X_A/EMP_R

Ability distribution

As is common in the literature we assume the work ability distribution, $\Gamma(\epsilon_R, \epsilon_{NRM})$, to be jointly log normal. Hence, there are five parameters to specify: two standard deviations, two means, and one correlation. Let σ_{ϵ_R} (μ_{ϵ_R}) be the standard deviation (mean) of the R ability, and σ_{NRM} (μ_{NRM}) be the standard deviation (mean) of the NRM ability, and

$\rho_{\epsilon_R,\epsilon_{NRM}}$ be the correlation between abilities. We note that the model is "scale free": the means of the distribution are irrelevant and we normalize them to unity. The correlation between the two abilities cannot be identified in the data. As such, we solve the model for various values of the correlation, $\rho_{\epsilon_R,\epsilon_{NRM}}$. Quantitatively, all of the results that we present here and in the policy experiments (Section 6) are virtually identical for different values of ρ. As such we proceed with a benchmark value of $\rho_{\epsilon_R,\epsilon_{NRM}} = 0$ and present robustness results in Appendix A.5

We identify the standard deviations, σ_{ϵ_R} and σ_{NRM}, iteratively as follows. Given initial guesses for these two parameters, we find the ability cutoffs, ϵ_R^* and ϵ_{NRM}^*, such that the model delivers the observed shares of low-skill workers (as identified in Section 2) in the routine and non-routine manual occupations in 1989 (with the share in labor force non-participation simply the residual).

That is, given the linearity of the wage and integral bounds in ability, ϵ_R, discussed in Section 4, the log of the routine wage can be written as:

$$log\omega_{\epsilon_R} = logD + log(\epsilon_R),$$

where D denotes a costant that is identical for all ϵ_R. This implies that the log wage is distributed:

$$\log\omega_{\epsilon_R} \sim N\left(\mu_{\epsilon_R} + \log D, \sigma_R\right),$$

and thus, the variance of observed wages is given by:

$$\mathrm{Var}\left(\log\omega_{R,\epsilon_R}|\log\epsilon_R > \log\epsilon_R^*\right) = \mathrm{Var}(\log D + \log\epsilon_R|\log\epsilon_R > \log\epsilon_R^*)$$

Given that D is a constant, this boils down to a variance in a truncated bivariate log normal:

$$\mathrm{Var}(\log\epsilon_R|\log\epsilon_R > \log\epsilon_R^*),$$

with a similar expressions for the variance of observed NRM wages. We iterate on the guesses of the standard deviations until the resulting truncated wages in the model match those in the data (the variance of the log observed wages for Routine workers in the data in 1989 is 0.237, while that for NRM equals 0.242). For notational purposes, let the ratio of identified ability cutoffs be denoted $m = \epsilon_{NR}^*/\epsilon_R^*$; this is used below.

Preferences

The model is calibrated to a monthly frequency. We set $\beta = 0.9957$, targeting an average annual risk free interest rate of 5%. We set $\sigma = 1$ so that preferences are logarithmic in consumption. Finally, recall that NRC/high-skill workers supply labor along the intensive margin. Their separable preferences over hours worked feature a Frisch labor supply elasticity of 0.5 (see Chetty et al. (2013)).

Frictional labor market parameters

We set the exogenous monthly separation rate, δ, equal to the 1989 rate of 0.02; this is the monthly transition rate from employment to unemployment in the CPS for workers whose last occupation was R or NRM. We assume a Cobb-Douglas matching function in each occupation-ability-specific market, with symmetric elasticity with respect to vacancies and unemployed, equal to 0.5 (e.g., Pissarides and Petrongolo (2001). Without loss of generality, we assume an identical matching efficiency across all markets equal to 1. We calibrate the tightness ratio to match an employment rate of 0.95 across all low-skill workers to match the evidence in Table 1. This implies a monthly job finding rate of 0.38 in all markets, which is the average

Government transfers

There are two types of transfers in the model to low-skill workers: unemployment insurance, specified as a replacement rate of occupation-and-ability specific earnings, and transfers to labor force non-participants. We set the replacement rate for all workers types to 0.5 which is the maximum allowed value in the U.S. The transfer to non-participants is set internally to ensure that, when calibrated to match the 1989 shares of workers in R, NRM, and NLF, the marginal ($\epsilon_R^*, \epsilon_{NRM}^*$) worker is indifferent between participating in the labor force and being unemployed.[16]

Taxes

Government transfers are funded by taxes on profit and labor income. The labor tax schedule is progressive. We set the tax on unemployment and non-participant transfer income to zero. The tax rate on NRM and R labor income is set at $T_R = T_{NRM} = 0.137$, approximately the average tax rate across the second to fourth quintiles of income, while for high-skill/NRC tax rate is set at $T_{NRC} = 0.267$ which is the average federal tax rate for the fifth quintile of income.[17] At each calculation of a steady state equilibrium (before and after the decline in ICT price) we allow the profit tax rate,T_π, to adjust such that it balances the government budget constraint.[18]

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[16] To put this into context, the resulting value of steady state consumption of the least able worker is equal to 0.37 of the average R wage.

[17] These tax rates are based on the estimates in the Congressional Budget Office distribution of household income in 2015.

[18] Since investment is fully deducted in the model, this change has no effect on the economy. For all policy experiments in Section 6 we keep this tax rate constant and balance the budget with distortionary labor taxation on the NRC group.

Depreciation rates

We use the specific capital depreciation rates estimated by Eden and Gaggl (2018) and target an annual depreciation rate of $\delta_A = 19\%$ for ICT capital, and $\delta_K = 6\%$ on non-ICT, "physical" capital.

Relative prices of capital

We use the same data to calibrate the initial relative price of ICT capital to consumption to equal $\phi_A^{1989} = 0.77$. Our measure of advancement in automation technology is the fall in the relative price of ICT capital between 1989 and 2017. Based on the estimate in Eden and Gaggl (2018) we feed in a fall in the ICT price such that $\phi_A^{2017} = 0.3244\phi_A^{1989}$.[19] We set the relative price of physical capital to $\phi_K = 1$.

Production and income share parameters

We have assumed that aggregate production is Cobb-Douglas with respect to non-ICT capital, K; its share parameter is calibrated directly from the income share data to $\gamma = 0.31$. As we discuss below, the NRM labor share of national income has not changed during our period of interest. As such, we set $\varsigma_2 = 0$ so that NRM input, Y_{NRM}, is also Cobb-Douglas in production.

The parameters $\eta, \alpha, f_R, f_{NRM}, \tau$ also determine various income shares. We normalize $f_{NRM} = 1$. The data moments we match are the shares of total labor income, Routine labor income, and ICT capital income in GDP, and the fact that, when calibrated to 1989, pre-polarization values, the ratio of ability cutoffs must satisfy:

$$\frac{\epsilon_{NRM}^*}{\epsilon_R^*} \equiv m = \frac{P_R f_R}{P_{NRM} f_{NRM}} \left(\frac{\daleth_R}{\daleth_{NRM}}\right)^{\frac{1}{1-\sigma}},$$

in steady state equilibrium.[20]

[19] We note that the estimates in Eden and Gaggl (2018) end in 2013. We extrapolate both the price series and capital series until 2017 based on the median growth rate in these two series in the post Great Recession period. As a robustness check we note that during period they overlap the relative chained price index of private fixed investment in information processing equipment and software behave in an almost identical way to the Eden and Gaggl (2018) series. See https://fred.stlouisfed.org/series/B679RG3Q086SBEA.

[20] This is akin to an RBC model where the disutility scaling parameter on labor supply is calibrated to match a given fraction of time spent in market activity in steady state.

Production function: elasticities

The remaining two parameters cannot be identified from first moments in the data: ν, which controls the elasticity of substitution between ICT capital and R labor services, and ς_1, which controls the elasticity of substitution between Y_{NRC} and the $X_A - Y_R$ composite.

To calibrate them, we feed in the observed ICT price fall and iterate over ν and ς_1 such that we match two moments: (i) our Section 2 result of the 0.63/0.37 split between NLF and NRM in accounting for the fall in R employment, and (ii) the observed change in the ratio of ICT capital per employed R worker between 1989 and 2017 of 7.14 (i.e an increase of over 600%). We find that the model matches these at values of $\nu = 0.46$ and $\varsigma_1 = -1.1$.

5.2 Model Results

In this subsection, we first present results on empirical moments that are not targeted in our model calibration and quantitative specification. We conclude with results on the model's welfare implications of advancement in automation technology, as captured by the fall in the relative price of ICT capital.

5.2.1 Quantities and prices

To evaluate the empirical relevance of the model, and the role of ICT price change as a driving force in automation, we consider several non-targeted moments, specifically: (i) the fall in R employment propensity among the low-skilled, (ii) the change in the labor share of national income (and its occupational composition), and (iii) the behavior of the average NRM-to-R wage ratio. Table 6 compares these non-targeted moments in the model to their values in the data. We note also that the model matches the elasticity of ICT capital to its price, also not targeted in the model calibration.[21]

Likelihood of working in Routine

With respect to the fall in the propensity of low-skill workers to work in Routine occupations, the model generates a fall of 7.85 percentage points (p.p.). As discussed in Section 2, because of the secular increase in female labor force participation, it is difficult to isolate the change in occupational employment propensity due to advances in automation for all low-skilled individuals. However, if we consider only non-NRC men, Table 1 indicates a 16 p.p. fall 1989 and 2017. The model accounts for about half of this fall.[22]

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[21] The empirical measure is calculated based on the ICT capital stock and relative price in Eden and Gaggl (2018) .

[22] If we consider the non gender-specific fall, then the model accounts for 35% of the propensity fall. Recall that, by construction, the model matches the way that the overall fall in R propensity is split NLF and NRM.

National Income Shares

Between 1989 and 2017, the share of GDP accruing as labor income fell by 4.3 p.p. (see, for example, Karabarbounis and Neiman (2013). The model, driven solely by the fall in the price of ICT capital, generates a fall of 2.44 p.p., slightly more than half of that observed in the data.

With respect to the composition of labor income, Eden and Gaggl (2018) show that changes were not evenly distributed across occupations. The routine occupational labor share of GDP fell dramatically by 9.51 p.p. between 1989 and 2017, more than twice that of aggregate labor's share. At the same time, the non-routine cognitive labor share rose by 4.17 p.p.; the share of GDP accruing to non-routine manual employment remained roughly constant, increasing by 0.67 p.p..

As in the data, the fall in the share of GDP accruing to routine occupational workers in the model (5.9 p.p.) is more than double the fall in aggregate labor (2.44 p.p.). Hence, the model accounts for roughly one-half to two-thirds of fall in aggregate and routine labor income share. Moreover, the model yields an increase in the share of income accruing to NRC labor of 3.5 p.p., very close to the change observed in the data.[23]

Relative wages

One of the stylized facts associated with job polarization is the decline in the wage gap between middle-class routine jobs and low-wage non-routine manual jobs. Based on CPS outgoing rotation group data, the relative average hourly wage of R to NRM workers fell by about 10 percent during our period of interest.[24]

To determine the model's prediction for relative wages, we first note that the the model generates a fall of 7.4% in the wage *per efficiency unit* of routine labor, ω_R, and an increase of 4.2% in the wage per efficiency units of NRM labor, ω_{NRM}. These efficiency measures, of course, are not the empirically observed measures. As such, using the equilibrium efficiency wages, cutoffs, and employment rates, we construct average wages as:

[23] Recall that the model is calibrated so that the NRM labor share of national income does not change.

[24] A similar fall, of approximately 12 percent, is observed in average hourly wages constructed from the March annual earning supplement of the CPS. We are grateful to Paul Gaggl for sharing this data with us.

$$E(\omega_R) = \frac{\omega_R \int_{\epsilon_R^*}^{\infty} \int_{-\infty}^{\epsilon_R+\log(m)} E\, R_{\epsilon_R} \epsilon_R \Gamma'(\epsilon_R, epsilon_{NR}) d\epsilon_{NRM} d\epsilon_R}{\int_{\epsilon_R^*}^{\infty} \int_{-\infty}^{\epsilon_R+\log(m)} \Gamma\,'(\epsilon_R, \epsilon_{NR}) d\epsilon_{NRM} d\epsilon_R},$$

$$E(\omega_{NRM}) = \frac{\omega_{NR} \int_{\epsilon_{NR}^*}^{\infty} \int_{-\infty}^{\epsilon_{NR}-\log(m)} E\, R_{\epsilon_{NRM}} \epsilon_{NRM} \Gamma'(\epsilon_R, epsilon_{NR}) d\epsilon_R d\epsilon_{NRM}}{\int_{\epsilon_{NRM}^*}^{\infty} \int_{-\infty}^{\epsilon_{NRM}-\log(m)} \Gamma\,'(\epsilon_R, \epsilon_{NRM}) d\epsilon_R d\epsilon_{NRM}}.$$

As Table 6 indicates, the average R to NRM wage ratio falls by 3.6%, accounting for about a third of the observed change in the data.

Output

Finally, what are the model's implications with respect to aggregate output? The fall in ICT price and the resulting equilibrium allocations increase GDP by 12%. By way of comparison, between 1989 and 2017, output per capita has risen by about 40% in the data. Hence, the model implies that about a quarter of the change in observed output can be attributed to advancement in automation technology, as proxied by the drop in the relative price of ICT capital.

	(1) Data	(2) Model
Employment		
Percent change in routine share (out of non-NRC)	-15	-7.85
Labor Shares (out of GDP)		
P.p change: Total	-4.3	-2.4
P.p change: Routine	-9.51	-5.9
P.p change: Non-Routine Cognitive	4.17	3.5
P.p change: Non-Routine Manual	0.67	0
Wages		
% change in average wage gap: Routine/Non-Routine Manual	-10	-3.6
GDP		
% change in real per-capital GDP	40	12
Elasticity of ICT capital w.r.t. price of ICT	0.40	0.41

Note: All changes are between 1989 and 2017.

5.2.2 Welfare

What does automation and the increase in aggregate output mean for welfare? We show that, despite rich model heterogeneity, our assumptions allow us to derive simple closed form solutions that characterize welfare. We then use these welfare measures to outline the heterogeneous welfare implications of advances in automation technology.

Measures of welfare

Recall that the steady state value of being unemployed, with ability ϵ_R, and searching for employment in the R occupational market is given by:

$$V_{u,\epsilon_R} = \frac{(f_R P_R \epsilon_R)^{1-\sigma}}{1-\beta} \daleth_R.$$

The steady state value of being employed is given by:

$$V_{e,\epsilon_R} = \left[\frac{\frac{\left(1-\beta(1-\mu(\theta_{\epsilon_R}))\right)}{1-\beta} \daleth_R - \frac{b^{1-\sigma}}{1-\sigma}}{\beta\mu(\theta_{\epsilon,R})} \right] (f_R P_R \epsilon_R)^{1-\sigma}.$$

Hence, the expected or average welfare of a labor force participant, with ability ϵ_R, who selects into the R occupation is a weighted average, with weights given by the unemployment and employment rates:

$$V_{\epsilon_R} = UR_{\epsilon_R} V_{u,\epsilon_R} + ER_{\epsilon_R} V_{e,\epsilon_R}.$$

Substituting in from above, the consumption equivalent value of utility is naturally given by:

$$C_{\epsilon_R} = \left[UR_{\epsilon_R} \frac{\daleth_R}{1-\beta} + ER_{\epsilon_R} \left[\frac{\frac{\left(1-\beta(1-\mu(\theta_{\epsilon_R}))\right)}{1-\beta} \daleth_R - \frac{b^{1-\sigma}}{1-\sigma}}{\beta\mu(\theta_{\epsilon_R})} \right] \right]^{\frac{1}{1-\sigma}} f_R P_R \epsilon_R.$$

A similar expression holds for labor force participants in the NRM occupation. This greatly simplifies the calculation of welfare and how they change across steady states.

We proceed as follows. Given the post-automation equilibrium cutoffs for $\epsilon_R^{*,NEW}$ and $\epsilon_{NRM}^{*,NEW}$, we simulate a billion low-skill individuals, drawing abilities from the calibrated joint log normal distribution. We then calculate the new steady state measures or NLF, R, and NRM as:

$$NLF^{NEW} = I\left(\epsilon_R \leq \epsilon_R^{*,NEW}\right) I\left(\epsilon_{NRM} \leq \epsilon_{NRM}^{*,NEW}\right)$$

$$NRM^{NEW} = I(log(m^{new}) + log(\epsilon_R) \leq log(\epsilon_2)) I\left(\epsilon_{NRM}^{*,NEW} \leq \epsilon_{NRM}\right)$$

$$R^{NEW} = I(log(m^{new}) + log(\epsilon_R) > log(\epsilon_2))I(\epsilon_R^{*,NEW} \leq \epsilon_R)$$

where $I(.)$ is an indicator function and $m^{new} = \frac{\epsilon_{NR}^{*,NEW}}{\epsilon_R^{*,NEW}}$. We identify those low-skill individuals who choose to remain in their original occupation, and those who switch occupations or leave the labor force. In particular, following the ICT price change, the switchers are: (i) those used to be R and become NLF, (ii) those who used to be R and become NRM, and (iii) those who used to be NLF and become NRM. We calculate the percent change in consumption equivalent welfare due to automation for each group separately.

Previously routine workers

Consider those who choose the routine occupational market both pre- and post-automation. Their ratio of post- to pre-automation welfare, denoted by $\Delta R^{OLD} \rightarrow R^{NEW}$, is given by:

$$\Delta R^{OLD} \rightarrow R^{NEW}$$

$$= \frac{\left[UR_{\epsilon_R} \frac{\daleth_R}{1-\beta} + ER_{\epsilon_R} \left[\frac{\frac{\left(1-\beta(1-\mu(\theta_{\epsilon_R}))\right)}{1-\beta} \daleth_R - \frac{b^{1-\sigma}}{1-\sigma}}{\beta\mu(\theta_{\epsilon_R})} \right] \right]^{\frac{1}{1-\sigma}} f_R P_R^{NEW} E(\epsilon_R)^{R^{OLD} \rightarrow R^{NEW}}}{\left[UR_{\epsilon_R} \frac{\daleth_R}{1-\beta} + ER_{\epsilon_R} \left[\frac{\frac{\left(1-\beta(1-\mu(\theta_{\epsilon_R}))\right)}{1-\beta} \daleth_R - \frac{b^{1-\sigma}}{1-\sigma}}{\beta\mu(\theta_{\epsilon_R})} \right] \right]^{\frac{1}{1-\sigma}} f_R P_R^{OLD} E(\epsilon_R)^{R^{OLD} \rightarrow R^{NEW}}}$$

$$= \frac{P_R^{NEW}}{P_R^{OLD}},$$

where $E(\epsilon_R)^{R^{OLD} \rightarrow R^{NEW}}$ denotes the average ability of those who remain in R. From equation (8), recall that labor market tightness, employment/unemployment rates, and $\daleth_R$ are invariant to changes in ϕ_A. Hence, the change in welfare is exactly the change in prices that final goods producers pay for routine labor input; these prices are translated 1-to-1 to routine worker wages, their consumption and (consumption equvalent) welfare. As indicated in the bottom panel of Column 1, Table 7, those who remain in R experience a 6.5% drop in welfare.

Welfare change derivations for those who switch occupations or labor force status are slightly more involved; details are provided in Appendix A.4 All results are displayed in the bottom panel of Column 1, Table 7.

Some R workers have relatively high NRM abilities; post-automation, they switch into NRM (as opposed to remaining R or leaving the labor force). These workers see an average fall in welfare as well (though smaller than those who remain R), amounting to 1% in consumption equivalent terms. Others who were previously R have relatively low NRM ability. After the fall in the return to R employment, they choose to exit the labor force. This group experiences an average welfare fall of 4%.

All other workers

Since NRM labor input is complementary to automation capital, the return to working (and searching) in that occupation rises. In the new steady state, all those who were previously in NRM choose to remain. Welfare increases by 5% for the average NRM stayer.

For most low-skill individuals who were out of the labor force, the fall in ICT capital price does not affect their participation choice. Since government transfers, b_o, are unchanged, their welfare is unchanged. However, those with sufficiently high NRM ability respond to the increase in the return to NRM labor, and switch to participating in the NRM occupational market. This group sees an average welfare increase of 3.2%.

Finally, high-skill workers benefit the most from the decline in the price of automation technology, experiencing a consumption equivalent welfare increase of 22%. This is not surprising since NRC labor input is a complement with ICT capital in production, and because they are the "capitalists" and hold all firm equity in the economy.

6. Policy Experiments

Given that we find an important quantitative role for automation, we use this new framework as a "laboratory" to consider a variety of government policies and their consequences for equilibrium allocations and welfare. We consider two sets of policies. First, we study the effects of a retraining program, targeted at improving the work ability (in a distributional sense) of the low-skilled. Second, we consider a broader set of redistribution policies that target transfers to the low-skilled. A number of these—such as reforms to the unemployment insurance system and the introduction of a universal basic income—have been discussed in the context of ameliorating inequality, and aiding those most negatively affected by automation.

Given the general equilibrium emphasis of the model, each of these policies must be financed through increased government taxation. Our approach is to do so through increased labor income taxes of high-skill (NRC) workers, those who have most benefited from automation. This is to be consistent with our interest in analyzing the effects of programs targeted toward those most adversely affected. This implies increasing the distortion on labor supply of high-skill workers.[25]

[25] We note that it is possible to completely undo all of the equilibrium effects of the fall in ϕ_A, through the introduction of a tax on purchases of ICT capital, τ_A. Increasing τ_A to exactly offset the fall in ϕ_A, leaving the effective ICT price unchanged, would return the economy to its pre-automation steady state values.

	ICT Change	Retraining	UI	UBI	NLF Benefits	Taxation
Cutoffs						
$\Delta\varepsilon^*_R$	6.70	-0.22	-3.95	10.77	26.37	-9.66
$\Delta\varepsilon^*_{NRM}$	-4.84	4.00	-4.51	9.45	26.66	-10.24
Labor states						
ΦNLF	2.19	-2.21	-2.20	5.84	15.12	-5.18
ΦR	-3.82	0.27	1.57	-4.69	-11.52	3.81
ΦNRM	1.64	1.94	0.64	-1.15	-3.60	1.37
Emp Rate: R	0.95	0.00	0.945	0.946	0.95	0.95
Emp Rate: NRM	0.95	0.00	0.945	0.946	0.95	0.95
ΔY_{NRC}	1.23	0.37	0.13	-13.87	-8.03	-2.06
ΔY_R	-3.72	0.60	-0.11	-5.03	-12.37	3.13
ΔY_{NRM}	7.14	5.02	-0.75	-4.01	-13.18	3.90
GDP						
ΔGDP	11.98	1.02	-0.06	-10.42	-10.04	0.29
NRC Labor Tax						
ΦLabor NRC Tax	0.00	-1.51	-0.50	35.19	25.00	9.98
Labor Share						
Φ Agg Labor Share	-2.44	0.01	-2.59	-1.63	-0.44	0.52
Wages						
$\Delta\omega_R$	-6.70	0.22	0.14	-7.22	3.42	-4.19
$\Delta\omega_{NRM}$	4.84	-4.00	0.70	-5.90	3.14	-3.61
$\Delta\omega_{NRC}$	23.24	0.83	-0.30	7.50	-3.79	4.45
$\Delta\omega_{NRC}$: After Tax	23.24	0.85	0.11	-12.80	-10.64	-2.82
ICT per R						
$\Delta X_A - \Delta Y_R$	196.05	0.41	0.26	-13.37	6.34	-7.77
Welfare: Consumption Equivalence						
Δ: R^{Old} -> R^{New}	-6.48	1.23	1.75	6.23	3.48	10.13
Δ: R^{Old} -> NRM^{New}	-0.95	NA	2.56	11.69	NA	10.45
Δ: R^{Old} -> NLF^{New}	-4.01	NA	NA	26.25	16.69	NA
Δ: NRM^{Old} -> R^{New}	NA	-1.17	NA	NA	3.33	NA
Δ: NRM^{Old} -> NRM^{New}	4.96	-3.25	2.43	7.43	3.18	10.78
Δ: NRM^{Old} -> NLF^{New}	NA	-1.99	NA	27.12	16.64	NA
Δ: NLF^{Old} -> R^{New}	NA	0.00	2.24	NA	NA	5.79
Δ: NLF^{Old} -> NRM^{New}	3.17	9.23	2.51	NA	NA	6.09
Δ: NLF^{Old} -> NLF^{New}	0.00	0.00	0.00	34.05	34.71	0.00
Δ: NRC^{Old} -> NRC^{New}	22.64	20.79	0.07	-21.89	-22.99	-4.98

Notes

Φ= Percentage Points change

Δ = Percenrate change

6.1 Retraining Program

Our first policy experiment changes the ability distribution of low-skill workers in the face of automation. We consider a change in the marginal distribution of ϵ_{NRM} ability (leaving the marginal distribution of ϵ_R unchanged), capturing the idea of training low-skill workers to do non-routine manual work.[26] In this retraining policy, we target those who are out of the labor force (i.e. have ability below both cutoffs $\epsilon_R^{*,NEW}$ and $\epsilon_{NRM}^{*,NEW}$) in the 2017, post-automation steady state.[27]

Starting from the post-automation steady state (described in Column 1 of Table 7), we "offer" an additive increase in NRM ability to non-participants. For those with relatively high ϵ_{NRM}, the increase would improve their ability sufficiently to induce them to join the labor force and seek employment in the NRM occupation; such workers would optimally select into the "retraining" treatment. Others with low ϵ_{NRM} would not. We search for the NRM ability increase that returns low-skilled labor force participation to its 1989, pre-automation value and we find that in order to return labor force participation back to its pre-automation level, an increase in ϵ_{NRM} that equals about a quarter of the standard deviation of NRM ability is required. This induces about 10% of non-participants to select into treatment.[28]

This experiment increases GDP by slightly more than 1%, through two effects. First, since both labor force participation and NRM ability increase (for those who transition from outside the labor force into NRM occupations), there is a direct effect on labor input and, hence, output. Second, given the complementarity of NRM labor with ICT capital, it increases the return to investment, leading to an increase in the ICT capital stock, further contributing to output growth.

In terms of welfare, the main beneficiaries are naturally non-participants who, through retraining, move into the NRM occupation. They experience an increase in consumption equivalent welfare of just over 9%. The second group to most benefit is the high-skilled, who experience a 2% increase in welfare. This is due to two channels. First, transfers to labor force non-participants are reduced, reducing their labor tax rate by about 1.5 p.p.. Second, the NRC wage increasing by almost 1 percent since they are complements in production to both NRM labor and automation capital.

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[26] The closest existing federal program would be the Trade Adjustment Assistance (TAA) program assisting workers in firms hurt by foreign trade. Among other benefits, this program pays for retraining. See for example the 2015 TAA benefits page: https://www.doleta.gov/tradeact/benefits/2015-amendment-benefits.cfm

[27] We view this as an empirically relevant exercise based on Card, Kluve and Weber (2018) who conduct a meta analysis of training programs, and find that training programs generally affect employment over longer horizons, with larger effect for the long-term unemployed (see, for example, Tables 3 and 9). These latter individuals are the most similar to the targeted individuals in our model analysis.

[28] Since the experiment results in an ability distribution that is no longer log normal, we cannot rely on closed form solutions of the bivariate log-normal distribution. Rather we rely on numerical simulation of one billion individuals and calculate the resulting equilibrium.

With respect to the low-skill, those who were *already* working in NRM prior to the experiment see a fall in welfare. This is due to a "crowding out" effect: the increase in the supply of NRM abilities leads to a fall in the efficiency price of their labor. This leads to an exit from the labor force of workers with NRM abilities that were close to the pre-retraining threshold. Still others are induced to switch to to the R occupation. The most negatively affected are those with sufficiently high ϵ_{NRM} that remain in the occupation, and suffer from the fall in their wages, income, and welfare. Finally, those who, prior to the retraining, were working in R see a small increase in welfare, since their labor is complementary to NRM labor.

Cost-benefit analysis

Since the existing literature provides little guidance regarding the appropriate "production function" (and hence cost structure) of retraining programs, our analysis abstracts from the policy experiment's cost. Yet, it is instructive to provide a proxy in terms of cost-benefit analysis.

This retraining induced an inflow from outside the labor force of approximately 10% (i.e. about 3% of the population), resulting in an increase of output of about 1%. This means that as long as the various per participant cost channels of the program (i.e. labor, capital and potential increases in tax distortions) amount to less than 30% of per capita GDP, the retraining program has a positive return from an aggregate perspective.

6.2 Redistributive Transfers

In this subsection we consider four redistributive, policies transferring resources from high-wage workers (who, as shown in Section 5, significantly benefit from automation) to middle- and low-wage workers. The four policies are: (i) a reform to the unemployment insurance system, (ii) the introduction of a universal basic income, (iii) increasing transfers to those outside of the labor force, and (iv) changes in the labor taxes levied on the low-skilled.

We begin with a change to unemployment insurance (UI hereafter) where workers receive an additional transfer while unemployed. We choose the size of this transfer so that the low-skilled labor force participation rate returns to its 1989, pre-automation level (as in Section 6.1). For comparability, we keep the "dollar value" of transfers per recipient fixed across remaining experiments.[29]

After discussing the UI program, we follow with a universal basic income (UBI hereafter) program where *every individual* receives a lump sum transfer, irrespective of her skill or labor force status. We then follow with an analysis of an increase in transfers to

[29] The qualitative effects across programs remains the same irrespective of the specific value we consider.

labor force non-participants. This subsection concludes with a discussion of a labor tax reform that increases the progressivity of the income tax system.

6.2.1 Unemployment Insurance Benefits

We consider an increase in the generosity of UI benefits whereby an additional transfer, $UI > 0$, is provided to each unemployed worker. This is in addition to the existing unemployment benefit modeled as a replacement rate relative to the worker type's wage. As an example, consumption of an unemployed routine worker of type ϵ_R becomes $C_{u,\epsilon_R} = b\omega_{\epsilon_R} + UI$. This additive term in the budget constraint (present also in the UBI analysis below) means the linearity of the solution approach discussed in Section 4 is no longer applicable. As a result: (i) each labor market (segmented by ϵ_R and ϵ_{NRM} for R and NRM occupations, respectively) features a different tightness ratio, and (ii) equilibrium cutoffs are no longer linear functions of ability. Solving for equilibrium requires additional numerical computation (e.g., numerical integration, spline approximation). [30]

Given concavity in preferences, the more generous UI system reduces the difference in utility between being employed and unemployed, a key object in the Nash bargaining problem. As a result, the bargained wage increases. Higher wages weaken firms' incentive to post vacancies at any ability level; job finding rates fall and unemployment rates rise. Overall, taking into account these changes, the increase in UI leads to an increase in the value of being unemployed.

What is the effect of the increase in the value of being unemployed on labor force participation? Unlike the UBI experiment discussed below, the value of being outside the labor force is not affected by change in the UI system. Ceteris paribus then, a more generous UI system leads to an increase in the value of participating in the labor force.

Before discussing the effects within the context of our GE model, it is useful to depict these forces in a simplified search and matching model without heterogeneity in production, taxes, or curvature in production (i.e a constant productivity in production). Specifically, we consider an individual who prior to any UI policy change is indifferent between being unemployed or being outside of the labor force. What are the effect of change in the UI policy in this economy?

First, we depict in Figure 1 the effect of a more generous UI system within this simplified model for the case where neither the tightness ratio, nor the wage react to this change in the environment. We label this case as the "partial equilibrium" in the DMP model (PE/DMP in the figure). As the figure depicts, the mere increase in UI benefits makes the value of unemployment increase vs. the value of non-participation (which does not change). This is depicted in the "$-x$" line in the bottom right panel in Figure 1 . Naturally, in this PE case, by construction, neither the wage, nor the job finding rate change, which is reflected by the straight lines in the top two panels.

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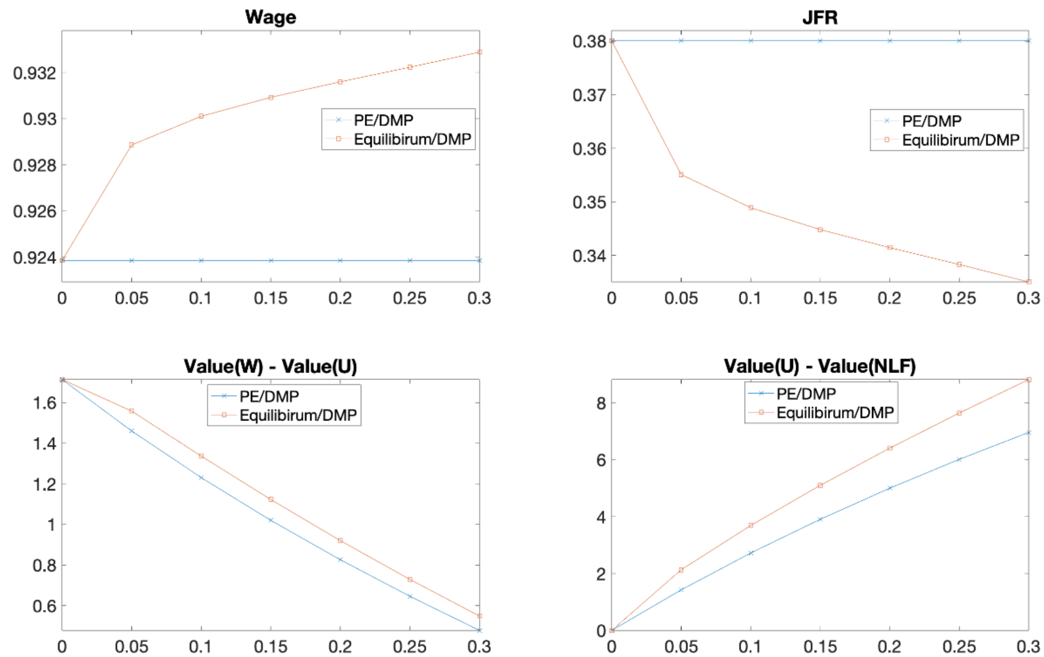
[30] Additional details are available upon request.

Figure 1: UI Policy



Notes: The x-axis depicts different UI transfers; a value of 0.3 matches the ratio of the UI transfer to the wage of the marginal Routine worker in our economy prior to the introduction of the program.

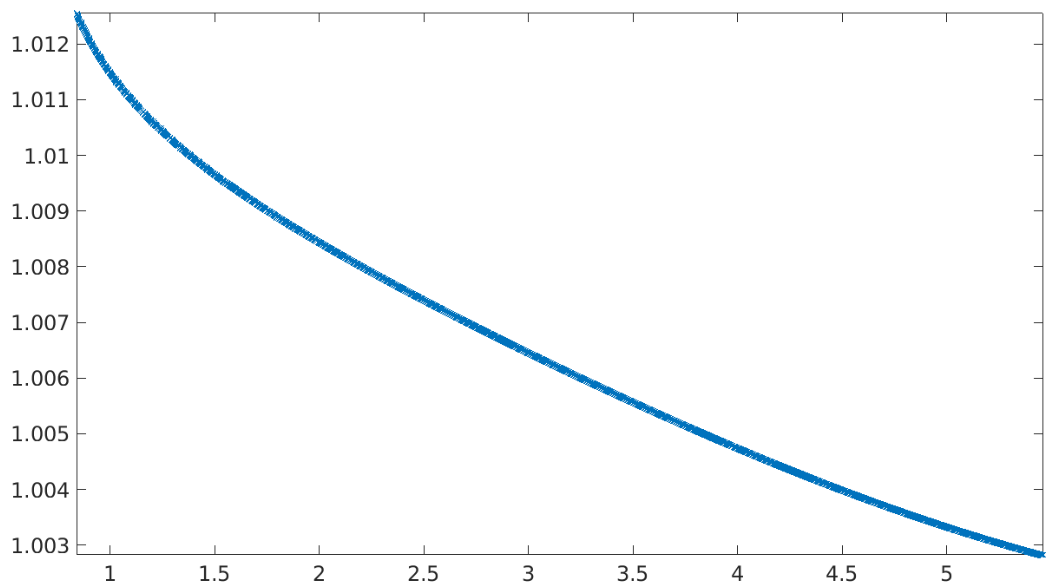
Consider now the case where we allow for the wage and tightness ratio to be a result of the bargaining problem between the firm and the worker, which is labelled as "Equilibirum/DMP" in the figure, and is depicted with the "— ▫ " line. The strengthening of the unemployment value, results in a higher bargained wage as the top left panel depicts. Since the worker's productivity does not change, this increase in the wage must result, via the free entry condition, in a fall in the tightness ratio, which manifests itself in a fall in the job finding rate in the top right panel. Overall, since the worker's bargaining position is improved even further vs. the PE case, this results in even a bigger increase in the value of unemployment vis-a-vis non participation as the bottom right panel depicts.

Column III in Table 7 reports the results of a more generous UI system within our full blown model economy. Since the increase in UI benefits increases the value of being unemployed, while the value of being outside the labor force is not affected, a more generous UI system leads to an increase in the value of participating in the labor force.[31]

[31] Quantitatively, we look for the value of the UI transfer that leads the labor force participation of the unskilled to return to its 1989 allocation. We find this value to be 25.7 percent of the average UI transfers in the economy. This value, which will also be used in

While labor force participation increases, the increase in UI benefits affects the wage and job finding rates. Figures 2 - 3 depict the equilibrium effects on the wage and the job finding rate of the more generous UI policy. Figure 2 displays the ratio of the new "post-policy" wage to the pre-policy (post-automation) wage, for each each routine ability level, ϵ_R. The wage increases at each ability (ranging from approximately 0.3% to 1.2%), though proportionately more at low ability levels as the additional transfer is a larger fraction of income.[32] The wage increase reduces the job finding rate as shown in Figure 3 For reference, the job finding rate was 0.38 at each ability level prior to the policy change. This fall in the job finding rate manifests itself as an increase in the unemployment rate, moreso at lower ability levels.

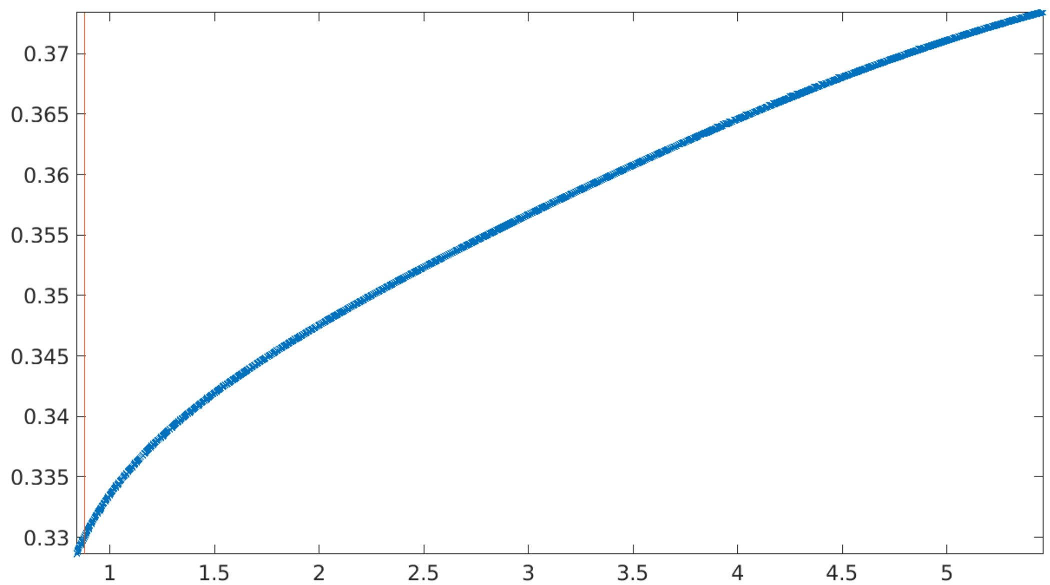
Figure 2: UI policy: Effects on the relative wage



the rest of the transfer experiments below, is equivalent to about 420 dollars per month in 2017.

[32] In the context of this UI experiment, quantitatively, a key channel through which these policies operate is via the bargaining problem and its impact on the wage and vacancies positing by firms. To discipline our analysis we require the model to match the elasticity of unemployment duration to unemployment benefits. See Appendix A.6 for a discussion.

Figure 3: UI policy: Effects on the relative JFR



Overall, as Table 7 reports, the introduction of the UI policy leaves aggregate output essentially unchanged (falling by less than one-tenth of one percent), despite the increase in labor force participation. This is due to the fact that the unemployment rate also increases. That is, the increased generosity of the UI program implies that conditional on participating in the labor force there is a fall in the employment rate. Hence, the change in the job finding rate due to the increased UI essentially cancels the increase in the labor force participation.

In terms of welfare, the UI policy has relatively modest effects, at least relative to the other experiments reported in Table 7. With respect to the low-skilled, the increase in the UI benefits, and its equilibrium effects on wages, dominate the increase in the unemployment rate; consumption equivalent welfare rises by about 2%, with small differences across groups.

Interestingly, high-skill workers see essentially no change in their welfare, rising by about 0.1%. While transfers to the unemployed increase, this is offset by reduced transfers to those outside the labor force. As a result, the tax rate and after-tax wage rate of the high-skilled are essentially unchanged.

To summarize, the increase in UI generosity is found to be welfare improving for all groups, though somewhat modest at the level required to match our labor force participation target.[33]

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[33] Given the model's inherent non-linearity, it is an open question as to how welfare would change for larger UI policy interventions.

6.2.2 Universal Basic Income

Our next experiment introduces a universal basic income. We model the UBI as an identical lump sum transfer, $UBI > 0$, to each individual, where to make policy experiments comparable we keep the transfer per person the same as in the UI policy case. As an example, the budget constraint for a routine worker of type ϵ_R becomes $C_{e,\epsilon_R} = \omega_{\epsilon_R}(1 - T_R) + UBI$.[34]

As the fourth column of Table 7 reports, the UBI program reduces GDP by almost 10 percent. This is primarily due to a fall in labor input, from both low- and high-skilled workers. What are the reasons for such a difference vs. the UI case analysed previosuly? As we discuss below, because of its budgetary implications, the UBI program requires a steep increase in the labor tax rate the NRC groups faces, leading to a fall in the supply of their hours worked which alters the return to labor force participation for the unskilled workers in the economy. Again, it is useful to first analyze these forces within the context of our simplified model as we did for the UI case in Figure 1. This time Figure 4 depicts the effects of the introduction of the UBI program.

Consider first the case of the PE. Under the UBI policy, individuals receive a transfer *unconditional* on their employment state. This induces a change in the value of employment, non-participation, as well as the value of being unemployed. One can show that as for CRRA utility functions this leads to an increase in the value of labor force participation. This is reflected in the bottom right panel where the value of unemployment minus the value of non-participation increases. Hence, PE forces would be pushing to an increase fall in participation.

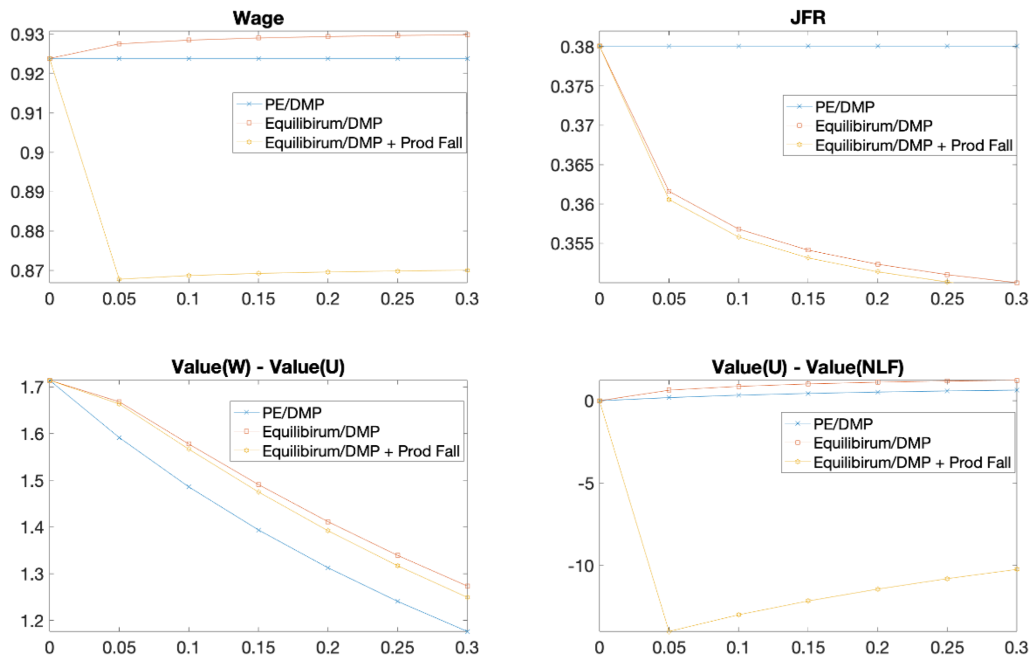
Consider now the Equilibrium/DMP case where the wage and tightness ratio are the resulting equilibrium objects to the bargaining problem between the worker and the firm and the free entry condition. As with the UI policy, the difference between being unemployed and employed falls due to the curvature in the utility function. This strengthens the worker's position and leads to an increase in the bargained wage and to a fall in the job finding rate. Overall, this increase in the value of unemployment, further increases the value of participation; as the bottom right panel depicts, in this Equilibrium/DMP case the value of unemployment minus the value of non-participation increases even further vis-a-vis the PE case. Hence, the DMP forces would be pushing to an even *bigger* increase in participation.

However, the introduction of UBI transfers to all individuals in the economy naturally needs to be financed. As we show below, in our full-blown model, this financing requirement induce a massive increase in the distortionary taxation NRC workers face, leading to a fall in their labor input. Because the NRC workers are complements to the

[34] As with the case of the UI policy, having an additive term in workers' budget constraints means that the linearity of the solution approach discussed in Section 4 is no longer applicable. We follow the same solution approach in Section 4. Moreover, this policy experiments adds a new expenditure term to the government budget constraint, eq. 6.

Routine and Non-Routine Manual workers, the significant fall in their labor input leads overall to a *fall* in the wages of Routine and Non-Routine Manual workers. To mimic this fall in productivity (which we show below in our full blown model economy) in this simplified version, we feed in a fall in the worker's productivity that matches the percentage fall in the worker's as in our model economy (of about 6 percent). This is depicted as the "Equilibrium/DMP + Prod Fall" in the figure; in his case, the fall in the wage is big enough to overturn the results discussed above; the value of non-participation increases vis-a-vis the value of being unemployed (and participating). This discussion highlights the importance of analysing the effects of UBI within a GE model with government budget constraints. Without considering the budgetary needs to finance the UBI program, its introduction would have led to an increase in labor force participation.

Figure 4: UBI Policy



UBI Policy Notes: The x-axis depicts different UI transfers; a value of 0.3 matches the ratio of the UI transfer to the wage of the marginal Routine worker in our economy prior to the introduction of the program.

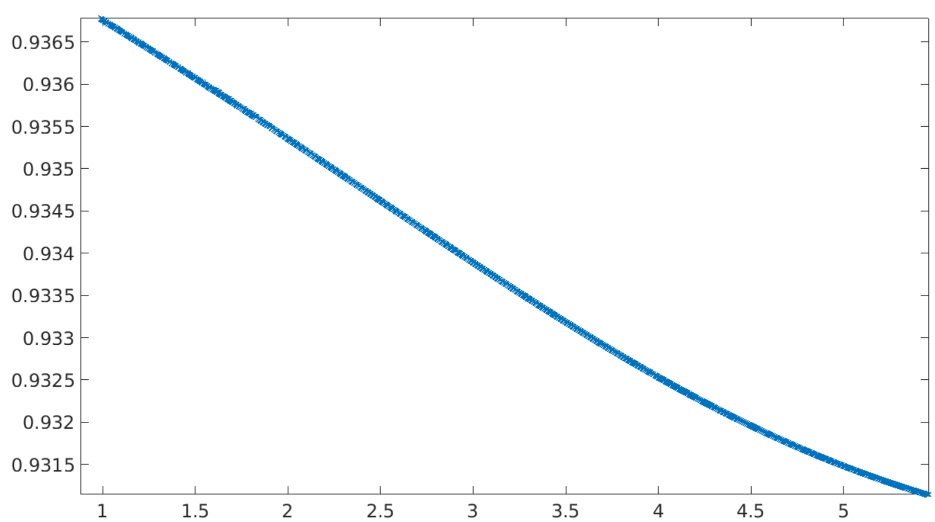
The overall effects in our model economy are presented in the fourth column in Table 7. The above discussion regarding the relative values of being unemployed or outside the labor force is reflected in the ability cutoff increasing, as the first two rows in Table 7. As before, all else equal, since workers receive the UBI *both* when they are unemployed and employed, the curvature in the utility implies that the increase in the value of unemployment versus employment improves the worker's outside option in Nash bargaining: wages increase, job creation falls, and unemployment rises (as in the previous UI experiment).

However, as Table 7 indicates there is no increase in ω_R and ω_{NRM} in equilibrium. As discussed above, this is because the primary effect of the UBI is its fiscal burden. Financing this transfer to all individuals requires a stark increase in taxation levied on the NRC workers; it has to increase by 35 percentage points in order to fund the UBI payment. This leads to an obvious fall in NRC labor input of about 13%. And since NRC labor input is complementary to routine and non-routine manual work, the large fall in high-skill labor supply reduces the marginal product of low-skill labor. As in the simplified model discussion above, this reduces the value of labor force participation.

Figures 5 - 6 depict the effects on the wage and the job finding rate of a more generous UBI system within our model economy respectively. Consider first Figure 5 which depicts the ratio of the new equilibrium wage to the pre UBI change wage, for each routine ability level, ϵ_R. The post UBI change wage falls for each ability, by about 6 percent though more so for the high ability levels as the UBI transfer amounts to a smaller fraction of income and thus strengths their bargaining position by less than the lower able workers.[35]

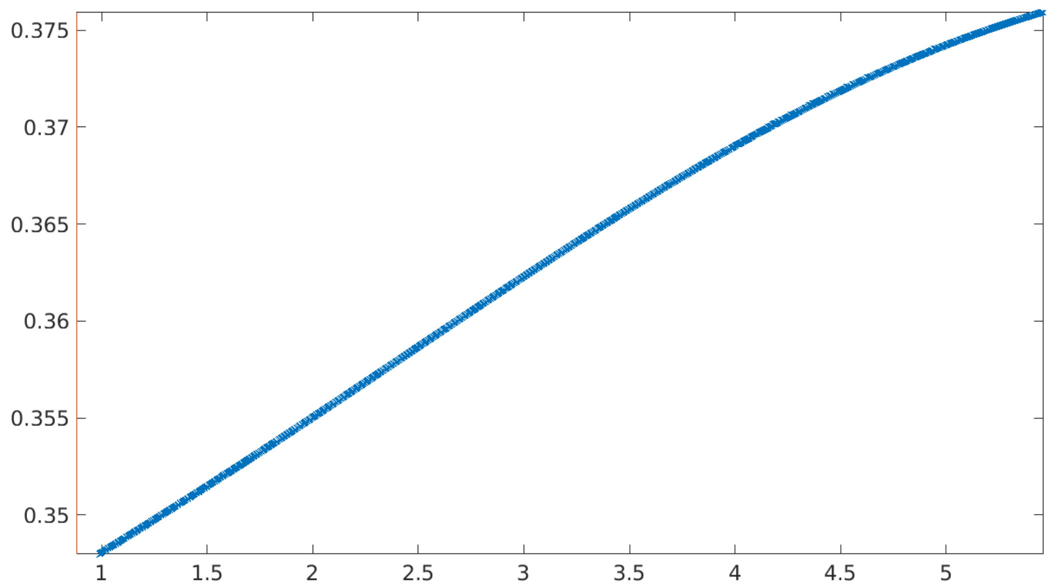
This fall in productivity of Routine workers lowers the job finding rate as shown in Figure 6 where we remind the reader that, prior to the introduction of the UI change the job finding rate was 0.38 for each ability. Since wages fall by more for higher ability Routine workers, their job finding rates fall by less relatively to lower ability Routine workers. Overall, naturally, this fall in the job finding rates for Routine workers manifests itself as an increase in the unemployment rate, more so at the lower ability levels.

Figure 5: UBI policy: Effects on the relative wage



[35] The fall in the productivity of Routine workers due to the fall in the supply of NRC workers is common to all Routine workers.

Figure 6: UBI policy: Effects on the relative JFR



Overall then, the introduction of the UBI program leads to an increase in the value of non-participation drawing workers out of the labor force; one that is several times larger than the effect of automation itself.

In terms of welfare, the UBI program delivers significant heterogeneity in effects. Although high-skill workers receive a UBI transfer, this is more than offset by the fall in after-tax labor income and equity income (as the economy's firm owners). They experience an approximate 22% consumption equivalent welfare reduction, similar in absolute magnitude to their welfare gain due to automation.

By contrast, the low-skilled experience significant welfare gains. These gains are present especially those who choose to remain in or transition toward labor force non-participation. However, even the unskilled who remain working enjoy an increase in their welfare (although their wages fall) from the mere fact that the UBI transfer is big enough vis-a-vis their wage and thus it accounts for a significant part of their income.

6.2.3 Transfers to non-participation

The next policy experiment is one in which transfers to labor force non-participants is increased. As before, the size of the increase is the same in dollar terms to those previously considered.

Not surprisingly, this program leads to a decrease in labor force participation as the fifth column in Table 7 reports; non-participation rises by 15 percentage points. To finance the program, the distortionary tax rate on high-skill labor increases by 25 p.p; this leads to a fall in NRC labor input. As a result of the decrease in both low- and high-skilled labor, aggregate output falls by 10%.

As with the UBI policy, the high-skilled see a large decrease in after-tax labor income and equity income. Their welfare falls by 23%. For the low-skilled, the greatest beneficiaries are those who choose choose labor force non-participation who enjoy a rise in welfare as in the UBI case. For those who remain in the labor force, the exit from participation of others increases their welfare modestly, via the equilibrium effect on their wages; overall this group's welfare increases by about half of their increase in the UBI case.

6.2.4 Progressivity of taxation

The policy experiments of Sections 6.2.2 and 6.2.3 indicate much room for redistribution; but such transfer programs come at a dramatic cost, in terms of aggregate output and distortionary welfare losses for high-skill workers. Here we explore an alternative way to redistribute resources that involves smaller output and welfare losses for the high-skilled. In our last experiment, we consider a more progressive tax system.

Specifically, we reduce the labor tax rate, $T_{NRM} = T_R$, that low-skill workers pay. To keep results comparable to those above, we reduce the average tax receipt from each worker by the same dollar value as the per recipient transfer of Sections 6.2.1 through 6.2.3. To accomplish this, the tax rate falls to essentially zero; for simplicity, we do this exactly and set $T_{NRM} = T_R = 0$. Maintaining government budget balance requires an increase in the labor tax rate levied on high-skill workers. In equilibrium, this amounts to a 10 p.p. increase, which is markedly smaller than those of Sections 6.2.2 and 6.2.3.

The sixth and final column in Table 7 reports the effect of this policy. The elimination of income taxation on low-skill workers naturally increases the value of employment relative to unemployment, and the value of participation relative to non-participation. This translates to an approximate five percentage point increase in their labor force participation and employment. In contrast, the tax increase on the high-skilled leads to a fall in their labor supply, but of lower magnitude than the cases of UBI and transfers to the NLF. These offsetting changes in employment/labor supply are reflected in the pre-tax wage rates earned in R, NRM, and NRC occupations. These offsetting changes also imply that there is essentially no impact on aggregate output.

In terms of welfare, this policy experiment delivers similar welfare gains to the low-skilled as the experiment of Section 6.2.3. But as opposed to gains being reaped disproportionately by those out of the labor force, increasing the progressivity of taxation favors those who remain and select into labor force participation. This experiment also results in much smaller welfare losses (on the order of 5%) for the high-skilled relative to the introduction of UBI or increasing transfers to non-participants.[36]

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[36] Of course, this is not the only tax system reform one could consider that might achieve redistribution while imposing small output and high-skill welfare losses. For instance, one might consider a tax cut (or wage subsidy) that is specific to the NRM occupation. This would have the potential of increasing labor force participation, while increasing the after-tax return to the lowest-wage occupational group, one that is likely less susceptible further

6.2.5 Summary and program comparison

To summarize, we use the model to evaluate macroeconomic and distributional impacts of various public policy proposals. A retraining policy, aimed at restoring labor force participation through improving the ability of workers in NRM occupations, is successful at doing so at relatively low "back-of-the-envelope" cost. It also increases aggregate income. However, it "crowds out" other low-skill workers, and it is unclear whether such a retraining program exists in practice at such a large scale.

A policy that increases the generosity of UI benefits is also able to restore labor force participation rates to "pre-automation" levels. It raises unemployment, has little impact on aggregate income, and is mildly welfare improving to all. By contrast, policies to introduce a UBI or increase the generosity of transfers to labor force non-participants reduce labor force participation, labor supply, and aggregate income. Moreover, they impose large welfare costs to the high-skilled. Finally, increasing the progressivity of the tax system has strong redistributive effects, raises labor force participation, has little impact on aggregate income, and imposes relatively small welfare losses to the high-skilled.

7. Conclusions

We consider the dramatic change in the occupational composition of employment—specifically, the disappearance of employment in middle-wage "routine" occupations—observed over the past 35 years. Empirically, we find that for individuals who were most likely to work in routine occupations, the decline in such job opportunities were offset by increased likelihood of both labor force non-participation and employment in low-wage non-routine manual occupations, with the former outcome exceeding the latter approximately 2-to-1.

We develop a heterogeneous agent macroeconomic model with investment in automation capital, labor force participation and occupational choice, and government policy. When subjected to the empirically observed change in the relative price of ICT capital, the model accounts for about half of the decline in routine employment, the fall in total labor's share of national income, and the divergent changes in occupational labor income.

We use this model to study the aggregate and distributional impact of various public policy proposals; our experiments are redistributive in nature as government budget balance is maintained through increased taxation of the high-skilled. While a number of programs—including retraining, and unemployment insurance and labor taxation reforms—are promising, proposals such as universal basic income are highly costly. We

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automation than others. Because the tax reduction is targeted and narrow in scope, it would be less costly in terms of additional tax distortions on the high-skilled. And because of the complementarity of the NRM occupation to other factors of production, it may significantly reduce (or reverse) the welfare loss to high-skill workers.

view our framework as useful for the evaluation of many other policies that can differ in implementation, intensity, and redistributive focus in the face of automation.

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