DISCUSSION PAPER SERIES

DP14362
(v. 2)

THE MACROECONOMICS OF AUTOMATION: DATA, THEORY, AND POLICY ANALYSIS

Nir Jaimovich, Itay Saporta-Eksten, Yaniv Yedid-Levi and Henry Siu

MACROECONOMICS AND GROWTH

MONETARY ECONOMICS AND FLUCTUATIONS

ISSN 0265-8003

THE MACROECONOMICS OF AUTOMATION: DATA, THEORY, AND POLICY ANALYSIS

Nir Jaimovich, Itay Saporta-Eksten, Yaniv Yedid-Levi and Henry Siu

Discussion Paper DP14362
First Published 28 January 2020
This Revision 17 April 2020

Centre for Economic Policy Research
33 Great Sutton Street, London EC1V 0DX, UK
Tel: +44 (0)20 7183 8801
www.cepr.org

This Discussion Paper is issued under the auspices of the Centre's research programmes:

- Macroeconomics and Growth
- Monetary Economics and Fluctuations

THE MACROECONOMICS OF AUTOMATION: DATA, THEORY, AND POLICY ANALYSIS

Abstract

During the last four decades, the U.S. has experienced a fall in the employment in middle-wage, "routine-task-intensive," occupations. We analyze the characteristics of those who used to be employed in such occupations and show that this type of individual is nowadays more likely to be out of the labor force or working in low-paying occupations. Based on these findings, we develop a quantitative, general equilibrium model, with heterogeneous agents, labor force participation, occupational choice, and investment in physical and automation capital. We first use the model to evaluate the distributional consequences of automation. We find heterogeneity in its impact across different occupations, leading to a significant polarization in welfare. We then use this framework as a laboratory to evaluate various public policies such as retraining, and explicitly redistributive policies that transfer resources from those who benefit from automation to those who bear the brunt of its costs. We assess the tradeoffs between the aggregate impact and welfare distributional consequences of such policies.

JEL Classification: N/A

Keywords: Polarization, automation, Routine Employment, labor force participation, universal basic income, Unemployment insurance, Retraining

Nir Jaimovich - nir.jaimovich@uzh.ch
University of Zurich and CEPR

Itay Saporta-Eksten - itaysap@tauex.tau.ac.il
Tel Aviv University and CEPR

Yaniv Yedid-Levi - yaniv.yl1@gmail.com
Interdisciplinary Center, Herzliya

Henry Siu - hankman.siu@gmail.com
University of British Columbia

Acknowledgements
We thank Adrien Aucert, Zsofia Barany, Gadi Barlevy, Larry Christiano, Max Dvorkin, Ester Faia, Yuriy Gorodnichenko, Zvi Hercowitz, Chad Jones, Joseba Martinez, Gabriel Mathy, Pete Klenow, Gianluca Violante, and numerous seminar audiences for helpful comments. All errors are our own.

The Macroeconomics of Automation: Data, Theory, and Policy Analysis*

Nir Jaimovich
University of Zurich and *CEPR*
nir.jaimovich@uzh.ch

Itay Saporta-Eksten
Tel Aviv University , *CEPR* and *IZA*
itaysap@tauex.tau.ac.il

Henry Siu
University of British Columbia and NBER
hankman@mail.ubc.ca

Yaniv Yedid-Levi
Interdisciplinary Center, Herzliya
yaniv.yl1@gmail.com

April 17, 2020

Abstract

During the last four decades, the U.S. has experienced a fall in the employment in middle-wage, "routine-task-intensive," occupations. We analyze the characteristics of those who used to be employed in such occupations and show that this type of individual is nowadays more likely to be out of the labor force or working in low-paying occupations. Based on these findings, we develop a quantitative, general equilibrium model, with heterogeneous agents, labor force participation, occupational choice, and investment in physical and automation capital. We first use the model to evaluate the distributional consequences of automation. We find heterogeneity in its impact across different occupations, leading to a significant polarization in welfare. We then use this framework as a laboratory to evaluate various public policies such as retraining, and explicitly redistributive policies that transfer resources from those who benefit from automation to those who bear the brunt of its costs. We assess the tradeoffs between the aggregate impact and welfare distributional consequences of such policies.

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

*We thank Adrien Aucert, Zsofia Barany, Gadi Barlevy, Larry Christiano, Max Dvorkin, Ester Faia, Yuriy Gorodnichenko, Zvi Hercowitz, Chad Jones, Joseba Martinez, Gabriel Mathy, Pete Klenow, Gianluca Violante, and numerous seminar audiences for helpful comments. All errors are our own.

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 focused 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 makes them prime candidates to be performed by automation technologies (see Autor, Levy and Murnane (2003), and the subsequent literature).

This paper contributes to our understanding of this phenomenon along three dimensions. First, while the literature has reached a near-consensus about the decline in routine employment and its link to automation, there is much less discussion about where workers who used to hold routine jobs end up working nowadays. To address this deficiency, we apply machine learning techniques that enable us to document that the likelihood of workers with "routine occupational characteristics" to work in routine occupations has fallen significantly. Instead, they are now either non-participants in the labor force or working at occupations that tend to occupy the bottom of the wage distribution. Our second contribution is to probe the quantitative distributional welfare impact of automation. To do so, we develop a rich, yet tractable, quantitative heterogeneous agent general equilibrium model. Given the significant role of labor force participation and occupation switching, the model endogenizes labor force participation, occupational choice, unemployment, and features endogenous investment. Our third contribution is to employ our new framework as a "laboratory" to evaluate various public policy proposals. 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 these three parts in detail. In Section 2, we survey the recent employment and occupation trends. We then proceed with our empirical analysis, using data from the Current Population Survey (CPS) during the "pre-polarization" period of 1984-1989, to train a machine learning algorithm to classify individuals into occupations in an agnostic manner. This mapping enables us to track the evolution of individuals with such "routine" characteristics over time. We then ask what has happened to the type of workers who would otherwise be employed in routine occupations during the "post-polarization" era. Our key finding is that the probability of such routine-type individuals working in routine occupations declined by about 16% between the pre-polarization era and the post-polarization one. 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 employed in non-routine manual occupations (which cluster at the bottom of the occupational wage distribution). Interestingly, we find that the unemployment rates for such workers remained roughly unchanged. We complement this analysis using the National Longitudinal Survey of the Youth (NLSY) 1979 and 1997 to demonstrate that similar patterns are observed for young low cognitive ability workers (as measured by AFQT scores), who formerly worked in routine occupations in the late 1980s.

These findings guide the setup and calibration of our general equilibrium model presented in Section 3. The model is developed with two goals in mind: first, to assess the distributional effects of advanced automation; and second, to quantify the effects of various policy reforms. In what follows we briefly describe below the structure of the model and the main welfare and policy results.

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) non-routine manual (NRM), that represent high, middle, and low paying jobs, respectively.[1] 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 and equilibrium wages, workers optimally decide whether or not to participate in the labor force and, conditional on doing so, sort into occupations. Firms in the model invest optimally in two types of capital: non-automation physical capital, and automation capital that is substitutable with R occupational labor. Thus, any channel that affects firms optimal adoption of automation capital affects the return to be working in a R vs. NRM occupation and the return to labor force participation. Labor force participants are either employed or unemployed due to search-and-matching frictions (Diamond (1982), Mortensen (1982) and Pissarides (1985)). 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 and in Section 4 and discuss its calibration in Section 5. In Section 6 we study the welfare impact of automation, which features significant heterogeneity in its welfare impact; workers who formerly labored in R occupations suffer a significant decline in their wages, and thus in their welfare. On the other hand, due to complementarity with automation technology, and to the capital ownership structure in the economy, NRC workers enjoy large increases in their welfare.

As such, in Section 7, the model is used as a laboratory to evaluate the aggregate and distributional effects

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

of various policies. We consider two sets of them, 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 targets labor force non-participants, and seeks to improve their ability in NRM work. It lures them back into the labor market, and improves their welfare. However, it harms others: a displacement effect implies that newly trained workers compete with those who already selected, prior to the retraining program, into NRM work, pushing down their wages, employment, and welfare.

The second set of policies is explicitly redistributive. It transfers 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) raising unemployment insurance benefits, (ii) introducing a universal basic income, (iii) increasing transfers to labor force non-participants, and (iv) making the tax system more progressive. While (i) modestly succeeds at improving the average welfare of all group, policies (ii) and (iii) impose large welfare losses on high-wage workers and are very costly in terms of aggregate income. In contrast, (iv) demonstrates that a (much) more progressive tax system, with a reduction in the taxes levied on low-earners and balancing the budget by increasing the taxes on high-earners, can achieve much of the redistribution gains without lowering aggregate output. It also leads to much smaller welfare losses for high-income earners.

Finally, Section 8 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)). An emerging literature has also begun to empirically evaluate the impact of automation and robotics on routine employment. For example, looking across countries, Michaels, Natraj and Van Reenen (2014) find that the larger the increase in ICT investment (at the industry-country level) is, the larger the increase in the high-skilled labor share and the decrease in the middle-skill share of labor income is (with insignificant effects on the least-skilled group). Graetz and Michaels (2018) use panel data of robot adoption across industries-country pairs, and find that robot penetration raises labor productivity, and have little effect on overall employment. Acemoglu and Restrepo

(2019) consider variation across US commuting zones and 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 reduces the number of workers who perform R tasks while rewarding workers engaged in non-routine, cognitive-intensive tasks.

While near-consensus exists in this literature about the drop in routine employment and its link to automation, less discussion has ensued about where workers who used to hold jobs with "routine occupational characteristics" in the 1980s (pre-polarization) end up working in recent years. Are they employed in other occupations? Are they unemployed more frequently? Are they likelier to have left the labor force altogether? These essential questions require answers from a policy perspective.

Cortes, Jaimovich and Siu (2017) take a step towards answering this question. They look at the evolution of routine employment within different pre-determined demographic groups and demonstrate that the decline in routine manual employment was concentrated among high school dropout men of all ages, and older high school graduate men. They show that in an accounting sense, men in this demographic group end up instead in low paying non-routine manual jobs, or not working at all. However, Cortes, Jaimovich and Siu (2017) pre-determined the specific demographic groups they analyzed, a major shortcoming of their research. Moreover, their analysis is limited to evolution within *these pre-determined demographics groups*. As such, in the analysis below we answer the question of where workers with 1980s "routine characteristics" end up, in an *aggregate* sense, without having to pre-determine the specific groups as in Cortes, Jaimovich and Siu (2017). To do that, we use a machine learning (henceforth ML) approach to classify individuals according to their *likelihood* of employment in various occupational groups based on their observed characteristics during the late 1980s. This mapping between characteristics and specific occupations enables us to track the actual employment and occupational choices of individuals with "routine characteristics" as automation advances.[2]

We classify prime-aged individuals (25-64 years of age) from the CPS into types based on their likeliest occupation in the pre-polarization era. This occupational classification draws distinctions based on task intensity according to two factors.[3] The first is whether an occupation is routine or non-routine. The

[2]An alternative approach would have been to use panel data and follow specific individuals from the late 1980s for three decades. This approach has two major drawbacks. 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.

[3]To obtain such a classification, we apply a random forest algorithm using age, education, gender, and race as observable

second relates to whether the task intensity 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) (see details in Appendix A.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 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 during it (see for example Cortes, Jaimovich and Siu (2017)). We then apply the algorithm to assign individuals to occupations in the remaining CPS subsamples. Doing so enables us to predict participation and occupational choices for all individuals had no changes in the economy occurred. We aggregate the results 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]

Columns (1) and (2) of Table A4 reveal the fraction of men, which were classified as likely to work non-NRC (low-skilled) in labor force non-participation, unemployment, and employment in NRC, NRM and R occupations comparing 1989 and 2017. Three important points emerge from this analysis. First, consistent with the findings in existing literature, we observe a large 10 percentage points (p.p) decline in employment in routine occupations within the low-skilled (*non-NRC*) group. Second, we observe no increase in the propensity of the low-skilled to participate in high-paying non-routine cognitive occupations. 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

characteristics in a flexible manner. We use the *ranger* implementation in R

[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. Appendix A.2.1 discusses ML classification errors, while Appendix A.2.2 discusses our algorithm for recovering "clean" aggregate series from data with ML classification errors. Moreover, as documented in Cortes (2016) and Cortes, Jaimovich and Siu (2017), large differences in characteristics exist between high- and low-skill worker types, whereas routine (cognitive 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 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 (averaged within each cell) does not play an important role.

changes account for the entire fall in R employment. Roughly two-thirds of the decline can be traced to the increase in NLF, and the rest by the increase in NRM employment. This is a key takeaway of our analysis: on average, low-skill types leaving R employment relocate into labor market statuses that are associated with lower income.[6] Third, the low-skilled experienced no obvious change in the unemployment rate, or in their unemployment-to-population ratio.[7] These three findings guide us in constructing and calibrating the model presented in the next section.

In Appendix A.3, we discuss the changes in employment and in occupational composition for women and for those classified as high-skilled. With respect to women, we find that their empirical patterns for women resemble those identified for men, but start later, around the year 2001 for reasons discussed in Appendix A.3. For the high-skilled, we encounter little evidence of an increase in non-participation or in employment in NRM, which suggests that the patterns observed for the low-skilled are linked to the routine employment decline.

A shortcoming of the ML approach is that it relies on workers' observed educational attainment—a variable that is potentially endogenous to the automation forces under consideration. We address this concern by using respondent's AFQT score as measured in the National Longitudinal Survey of Youth (NLSY); the AFQT measure is arguably a more direct and exogenous proxy for cognitive ability. The NLSY sample is too small for our ML approach, so we revert to a different method in the spirit of Cortes, Jaimovich and Siu (2017).[8] Looking at men in NLSY 1979, we recognize that the propensity to work in routine or non-routine manual occupations (the equivalent of our "low-skilled" in the CPS) is highest for those in the second to fourth deciles of AFQT (82% of employed). Table A7 compares the labor market status and occupational composition for workers in these deciles during 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 (of 16% as in the CPS analysis above), accompanied by greater 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 so displays greater labor force attachment.

[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 types of workers - Routine (R), Non-Routing Manual (NRM) and Non-Routine Cognitive (NRC) based on their last occupation prior to the unemployment spell.

[8]See Appendix A.4 for a detailed discussion about the NLSY analysis

3. Model

In this section, our goal is to setup a model environment for analyzing the heterogeneous welfare effects of automation and evaluating the impact of a wide set of policies meant to assist those ill-affected by automation.

Motivated by the findings of Section 2, which indicate 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). The low-skilled are heterogeneous as each worker is endowed with two ability parameters (productivity draws from a distribution)—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-skill occupation and participation choices depend on job finding probabilities and the equilibrium compensation in each job when employed. While Section 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 below.

Capital inputs in the forms of automation capital and non-automation capital are used in final production. Both capital stocks are owned by perfectly competitive, final good producers who make investment decisions. In the model therefore, the degree of automation capital accumulation is endogenous.

For tractability, we assume that 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 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), own the vast majority of assets in the

[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 the 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.

U.S.

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, and transfers to labor force non-participants.

Our modelling approach is related to the recent contributions by Eden and Gaggl (2018) and vom Lehn (2019). These papers consider representative agent frameworks where labor supply is inelastic and the labor choice is along the margin of which occupation to work in, without a labor force participation or an unemployment margin. By contrast, given our interest in welfare and policy analysis, we consider a heterogeneous agent economy with an empirically realistic distribution of income: high-skill individuals own capital and firms and low-skill individuals earn labor income and receive government transfers. Moreover, individuals in our model are not assumed to work and may find themselves employed, unemployed, or out of the labor force.

These elements are crucial for the following reasons. First, the empirical analysis referenced above suggested that labor force participation is the key margin of employment adjustment for the routine-type workers. Second, allowing for heterogeneity in the economy, as well as labor force participation and unemployment, is critical for the welfare analysis if one is to consider the implications of policy changes, such as the effects of 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 recent proposals for "universal basic income") must be financed through progressive labor and capital/profit taxation. This permits us to use the model as a laboratory for policy evaluation.

3.1. Final good producers

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

$$Y_t = F(K_t, X_{A,t}, Y_{NRC,t}, Y_{R,t}, Y_{NRM,t}) \tag{1}$$

Final good producers accumulate physical and automation 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-automation capital is denoted ϕ_K and the relative price of automation

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

capital is ϕ_A, where the final good is the numeraire ($P_Y = 1$). Hence, denoting by the "prime notation" a next period's variable, the firm's per-period profit is:

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

with the prices of intermediate goods given by P_R, P_{NRC}, P_{NRM}. The firm accumulates physical and automation capital and its dynamic problem is then given by

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

where T_π is a tax rate on firms' profits, β is the discount factor, and $\Lambda = \{\phi_K, \phi_A, T_\pi, P_R, P_{NRM}, P_{NRC}\}$ 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] Moreover, since our analysis below is across steady states we already impose the stochastic discount factor being equal to β.[12]

3.2. Intermediate goods production

3.2.1. Routine intermediate good producers

Intermediate good producers produce the routine intermediate good, Y_R and sell it to the final good firm. To do so, they 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 $\Gamma(\varepsilon_R, \varepsilon_{NRM})$; 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. That is, there is full information about worker abilities, which enables unemployed workers and vacancies to meet in occupation-*and-ability*-specific matches.

To avoid cluttered notation, we introduce the firm decision problem assuming steady state wages, thus using ω_{R,ε_R} and $\omega_{R,\varepsilon_{NRM}}$ to represent wages paid for R workers with ability ε_R and for NRM workers with ability ε_{NRM} respectively.[13]

[11] Because profits are taxed net of investment costs, there are no equilibrium effects on optimal capital demand. For a a similar approach see Abel (2007).

[12] 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.

[13] Generally, this setup implies that within each occupation, wages are specific for each combination of ε_R and ε_{NRM}. However, as discussed in Section (4), our quantitative analysis will focus on steady state equilibrium, implying that there are no transitions across occupations (only between employment and unemployment states within an occupation). Thus, in this case, the bargained wage of an individual, within a given occupation, is not a function of her productivity in the other occupation.

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, $M\left(v_{\varepsilon_R}, u_{\varepsilon_R}\right)$, 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 in the literature, firms take the tightness ratio, $\theta_{\varepsilon_R} \equiv \frac{v_{\varepsilon_R}}{u_{\varepsilon_R}}$, and the vacancy filling probability $q\left(\theta_{R,\varepsilon_R}\right)$ as given.

A matched firm and worker (with ability ε_R) produce $y_{\varepsilon_R} = f_R \varepsilon_R$ units of the R good, where f_R is an identical productivity parameter 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 $P_R f_R \varepsilon_R - \omega_{R,\varepsilon_R}$.

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:

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

subject to the law of motion:

$$x'_{\varepsilon_R} = (1-\delta)\, x_{\varepsilon_R} + v_{\varepsilon_R} q\left(\theta_{\varepsilon_R}\right).$$

Here δ is the exogenous match separation probability (that is common across good-ability-specific matches).[14] The quantity of efficiency-weighted R labor input is then given by:

$$Y_R = f_R (1 - Pop_{NRC}) \int_{\varepsilon_R^*}^{\infty} \int_{-\infty}^{\varepsilon_{NRM}(\varepsilon_R)} ER_{\varepsilon_R} \varepsilon_R \Gamma'(\varepsilon_R, \varepsilon_{NRM}) d\varepsilon_{NRM} d\varepsilon_R, \tag{2}$$

where Pop_{NRC} denotes the population share of high-skilled workers, $\Gamma'(\varepsilon_R, \varepsilon_{NRM})$ denotes the density function associated with the distribution function, Γ, and $ER_{\varepsilon_R} = \frac{x_{\varepsilon_R}}{\left(x_{\varepsilon_R} + u_{\varepsilon_R}\right)}$ denotes the employment rate (per labor force participant) for a given ability level, ε_R (recall that x_{ε_R} denotes the measure of individuals with ability ε_R that are working while u_{ε_R} denotes the measure of individuals with ability ε_R who are unemployed).

[14] The first order condition implies the optimality condition for vacancy posting:

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

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. Moreover, 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.

As shown 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 (2) the term ε_R^* denotes the cutoff ability in R such that all those with lesser ability do not work in R; the function $\varepsilon_{NRM}(\varepsilon_R)$ 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.

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.

3.2.2. Non-Routine Cognitive intermediate good producers

Since our primary interest is in the low-skilled labor market, we assume for simplicity's sake 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.

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 indicate that the high-skilled experience very low unemployment, unchanged over time. Given this, we abstract from search-and-matching frictions. Our ultimate interest is in accounting for the general equilibrium effects of various policy proposals, that must be financed through (progressive) distortionary income taxation. We therefore 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, with preferences over consumption, C_{NRC} denoted by the utility $U\left(C_{NRC}\right)$, and derive disutility from hours spent working,

L_{NRC} denoted by $G(L_{NRC})$.[15] 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 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:

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

3.3.2. Routine and Non-Routine Manual workers

Let $(\varepsilon_R, \varepsilon_{NRM})$ denote a worker's (constant) idiosyncratic ability draw pair. Given these draws 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 $V_{e,\varepsilon_R,\varepsilon_{NRM}}(\Lambda)$ denote the value of being an employed R worker for a worker with the productivities $(\varepsilon_R, \varepsilon_{NRM})$ where we remind the reader that $\Lambda = \{\phi_K, \phi_A, T_\pi, P_R, P_{NRM}, P_{NRC}\}$, denotes the collection of aggregate state variables that workers take parametrically; for simplicity's sake we denote the chosen occupation for such an individual by the first subscript of the two productivities draw. Then, similarly, $V_{u,\varepsilon_R,\varepsilon_{NRM}}(\Lambda)$ denotes the value of being an unemployed R worker for such an individual, $V_{e,\varepsilon_{NRM},\varepsilon_R}(\Lambda)$ the value of being an employed NRM worker for this individual, and $V_{u,\varepsilon_{NRM},\varepsilon_R}(\Lambda)$ is the value of being an unemployed NRM worker for this individual. Let the value of labor force non-participation be $V_{\varepsilon_O}(\Lambda)$, The value of being employed as an R worker is then given by:

$$
\begin{aligned}
V_{e,\varepsilon_R,\varepsilon_{NRM}}(\Lambda) \; &= U\left(C_{e,\varepsilon_R}\right) + \beta\delta\left[\max\left\{V_{u,\varepsilon_R,\varepsilon_{NRM}}\left(\Lambda'\right), V_{u,\varepsilon_{NRM},\varepsilon_R}\left(\Lambda'\right), V_{\varepsilon_O}\left(\Lambda'\right)\right\}\right] + \\
&\beta(1-\delta)\left[\max\left\{V_{e,\varepsilon_R,\varepsilon_{NRM}}\left(\Lambda'\right), V_{u,\varepsilon_R,\varepsilon_{NRM}}\left(\Lambda'\right), V_{u,\varepsilon_{NRM},\varepsilon_R}\left(\Lambda'\right), V_{\varepsilon_O}\left(\Lambda'\right)\right\}\right].
\end{aligned}
$$

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

$$C_{e,\varepsilon_R} = \omega_{\varepsilon_R}\left(1 - T_{\varepsilon_R}\right),$$

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

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

worker has the choice of remaining matched in the following period, leaving to unemployment, or leaving the labor force. Given our interest in steady state comparison, an employed worker will never switch from employment in one sector to another.

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

$$\begin{aligned} V_{u,\varepsilon_R,\varepsilon_{NRM}}(\Lambda) = {} & U(C_{u,\varepsilon_R}) + \beta(1-\mu(\theta_{\varepsilon_R}))\left[\max\left\{V_{u,\varepsilon_R,\varepsilon_{NRM}}(\Lambda'), V_{u,\varepsilon_{NRM},\varepsilon_R}(\Lambda'), V_{\varepsilon_O}(\Lambda')\right\}\right] + \\ & \beta\mu(\theta_{\varepsilon_R})\left[\max\left\{V_{e,\varepsilon_R,\varepsilon_{NRM}}(\Lambda'), V_{u,\varepsilon_R,\varepsilon_{NRM}}(\Lambda'), V_{u,\varepsilon_{NRM},\varepsilon_R}(\Lambda'), V_{\varepsilon_O}(\Lambda')\right\}\right], \end{aligned}$$

subject to:

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

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 the NRM occupation, or unemployed and choose to search in this 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:

$$V_{\varepsilon_O}(\Lambda) = U(C_o) + \beta\left[\max\left\{V_{u,\varepsilon_R,\varepsilon_{NRM}}(\Lambda'), V_{u,\varepsilon_{NRM},\varepsilon_R}(\Lambda'), V_{\varepsilon_O}(\Lambda')\right\}\right],$$

subject to:

$$C_o = b_o.$$

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:

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

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

$$\tilde{V}_{\varepsilon_R}\left(\Lambda\right)=V_{e,\varepsilon_R,\varepsilon_{NRM}}\left(\Lambda\right)-\left[\max\left\{V_{u,\varepsilon_R,\varepsilon_{NRM}}\left(\Lambda\right),V_{u,\varepsilon_{NRM},\varepsilon_R}\left(\Lambda\right),V_{\varepsilon_O}\left(\Lambda\right)\right\}\right].$$

The worker's outside option is the optimal choice between 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:

$$\max_{\omega_{\varepsilon_R}}\left[\tilde{V}_{\varepsilon_R}\left(\Lambda\right)\right]^{\tau}\left[\frac{\partial J\left(x_{\varepsilon_R},\Lambda\right)}{\partial x_{\varepsilon_R}}\right]^{1-\tau}. \tag{3}$$

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:

$$UI_{NRM}=\left(1-Pop_{NRC}\right)\int_{\varepsilon^*_{NRM}}^{\infty}\int_{-\infty}^{\varepsilon_R(\varepsilon_{NRM})}UR_{\varepsilon_{NRM}}b\omega_{\varepsilon_{NRM}}\Gamma'(\varepsilon_R,\varepsilon_{NRM})d\varepsilon_R d\varepsilon_{NRM},$$

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

$$UI_R=\left(1-Pop_{NRC}\right)\int_{\varepsilon^*_R}^{\infty}\int_{-\infty}^{\varepsilon_{NRM}(\varepsilon_R)}UR_{\varepsilon_{NRM}}b\omega_{\varepsilon_R}\Gamma'(\varepsilon_R,\varepsilon_{NRM})d\varepsilon_{NRM}d\varepsilon_R,$$

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

$$NLF=\int_{-\infty}^{\varepsilon^*_R}\int_{-\infty}^{\varepsilon^*_{NRM}}\Gamma'(\varepsilon_R,\varepsilon_{NRM})d\varepsilon_{NRM}d\varepsilon_R,$$

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:

$$Rev_{NRM}=\left(1-Pop_{NRC}\right)\int_{\varepsilon^*_{NRM}}^{\infty}\int_{-\infty}^{\varepsilon_R(\varepsilon_{NRM})}ER_{\varepsilon_{NRM}}T_{\varepsilon_{NRM}}\omega_{\varepsilon_{NRM}}\Gamma'(\varepsilon_R,\varepsilon_{NRM})d\varepsilon_R d\varepsilon_{NRM},$$

and :

$$Rev_R = (1 - Pop_{NRC}) \int_{\varepsilon_R^*}^{\infty} \int_{-\infty}^{\varepsilon_{NRM}(\varepsilon_R)} ER_{\varepsilon_R} T_{\varepsilon_R} \omega_{\varepsilon_R} \Gamma'(\varepsilon_R, \varepsilon_{NRM}) d\varepsilon_{NRM} d\varepsilon_R,$$

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:

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

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

Tax revenue from the final good producer is given by:

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

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

$$NLF b_o + UI_{NRM} + UI_R = Rev_{NRC} + Rev_R + Rev_{NRM} + Rev_\pi + Rev_{\pi_R} + Rev_{\pi_{NRM}}. \tag{4}$$

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 the the NRC intermediate good and receive a market wage equal to their marginal revenue product.

Each low-skill agent is endowed with a pair of idiosyncratic productivity parameters, ε_R and ε_{NRM}, drawn from a joint distribution $\Gamma(\varepsilon_R, \varepsilon_{NRM})$. 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, $\Gamma(\varepsilon_R, \varepsilon_{NRM})$, 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 $\{\omega_{\varepsilon_R}, \omega_{\varepsilon_{NRM}}\}$ for all $\varepsilon_R, \varepsilon_{NRM}$;
- tightness ratios, $\{\theta_{\varepsilon_R}, \theta_{\varepsilon_{NRM}}\}$, and vacancies, $\{v_{\varepsilon_R}, v_{\varepsilon_{NRM}}\}$, for all $\varepsilon_R, \varepsilon_{NRM}$;
- worker quantities, $\{C_{NRC}, L_{NRC}, B_{NRC}, C_o\}$ and $\{C_{e,\varepsilon_R}, C_{u,\varepsilon_R}, C_{e,\varepsilon_{NRM}}, C_{u,\varepsilon_{NRM}}\}$ for all $\varepsilon_R, \varepsilon_{NRM}$;
- labor input, x_{NRC} and $\{x_{\varepsilon_R}, x_{\varepsilon_{NRM}}\}$ for all $\varepsilon_R, \varepsilon_{NRM}$;
- firm quantities, $\{Y, Y_{NRC}, Y_R, Y_{NRM}, K, X_A\}$; and
- policy, $\{T_\pi, T_{NRC}, b, b_o\}$ and $\{T_{\varepsilon_R}, T_{\varepsilon_{NRM}}\}$ for all $\varepsilon_R, \varepsilon_{NRM}$

such that

- final good and intermediate good firms are profit maximizing (and in particular, physical capital accumulation, automation capital accumulation, and vacancy creation are optimal),
- workers are utility 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:

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

- labor market of the three factors of production clears,
- 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 imply that unemployment rates do not vary as automation capital prices fall. These conditions allow us to match the empirical unemployment patterns documented in Section 2. The three conditions are: (i) a constant relative risk aversion (hereafter CRRA) function, $U(.)$, (ii) vacancy costs, $\kappa_{\varepsilon_R}, \kappa_{\varepsilon_{NRM}}$ for all $\varepsilon_R, \varepsilon_{NRM}$, 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) as modelled above. When turning to the policy analysis in section 7 we remove this last assumption when relevant so that unemployment can respond to policy changes. We refer the reader to Appendix A.5 for the derivations of the expressions in this section.

4.1. Wages and tightness ratios

Recall the bargaining problem characterizing the R occupation, equation (3). As we show in Appendix A.5, the resulting wage for an R worker with ability ε_R is:

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

This is an increasing function of the worker's marginal revenue product, $f_R \varepsilon_R P_R$, 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.

As shown in Appendix A.5, given our sufficient set of assumptions, the equilibrium tightness ratio in the R market (similar expressions hold for the NRM market as well) is independent of productivities and capital prices and it implicitly solves:

$$\left[\frac{1-\beta(1-\delta)}{q(\theta_{\varepsilon_R})} + \beta \frac{\theta_{\varepsilon_R}}{1+\frac{(1-\tau)}{\tau(1-\sigma)}} \right] \kappa_0 = \beta \frac{\frac{(1-\tau)}{\tau(1-\sigma)}}{1+\frac{(1-\tau)}{\tau(1-\sigma)}}, \quad \forall \varepsilon_R. \tag{5}$$

where $\kappa_0 > 0$ is an exogenous parameter. Thus, the model yields a constant tightness ratio for each occupation in steady state, even as automation technology changes, making it consistent with the empirical patterns of the unemployment rate discussed in Section 2. It then follows that the wage function (6) results in a simple and tractable expression that is linear in worker ability, ε_R

$$\omega_{\varepsilon_R} = \frac{1}{1+\frac{(1-\tau)}{\tau(1-\sigma)}} \left[f_R + \theta_{R,\varepsilon_R} f_R \kappa_0 \right] \varepsilon_R P_R. \tag{6}$$

4.2. Productivity cutoffs

In Appendix A.6 we show that the steady state values of unemployment can be expressed as:

$$V_{u,\varepsilon_R,\varepsilon_{NRM}} = \frac{(f_R\, P_R \varepsilon_R)^{1-\sigma}}{1-\beta} \daleth_R(\varepsilon_R),$$
$$V_{u,\varepsilon_{NRM},\varepsilon_R} = \frac{(f_{NRM} P_{NRM} \varepsilon_{NRM})^{1-\sigma}}{1-\beta} \daleth_{NRM}(\varepsilon_{NRM}),$$

for all $\varepsilon_R, \varepsilon_{NRM}$ where $\daleth_R(\varepsilon_R)$ and $\daleth_{NRM}(\varepsilon_{NRM})$ are functions of exogenous parameters. This permits us to establish the following results. Recall that transfers to labor force non-participants are independent of ability, so the value of non-participation is independent of ability. We can thus solve for cutoff values ε_R^* and ε_{NRM}^* such that a worker with ability $\varepsilon = (\varepsilon_R, \varepsilon_{NRM})$ below both cutoffs prefers labor force non-participation. These cutoffs are given by:

$$\varepsilon_R^* = \frac{1}{f_R P_R} \left(\frac{b_o}{\daleth_R} \right)^{\frac{1}{1-\sigma}},$$
$$\varepsilon_{NRM}^* = \frac{1}{f_{NRM} P_{NRM}} \left(\frac{b_o}{\daleth_{NRM}} \right)^{\frac{1}{1-\sigma}}.$$

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 $V_{u,\varepsilon_{NRM}}$. Specifically, for each $\varepsilon_R (> \varepsilon_R^*)$ there exists an $\hat{\varepsilon}_{NRM}$ such that for $\varepsilon_{NRM} < \hat{\varepsilon}_{NRM}$, the worker chooses unemployment in R, and for $\varepsilon_{NRM} \geq \hat{\varepsilon}_{NRM}$ the worker searches in NRM. This cutoff is the solution to:

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

implying a linear function of the form:

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

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 and production, and frictions in the labor market.

4.3. Welfare

What does a decline in the price of automation capital mean for welfare? A direct effect of this increased productivity is greater aggregate output. At the same time, depending on the substitutability of workers of different types with automation capital, it can result in "winners and losers." In this section we show that, despite the rich model heterogeneity, our assumptions enable us to derive simple closed form solutions that characterize the changes in welfare due to the impact of advances in automation technology. The discussion centers on welfare changes for previously routine workers,

Consider those who choose the routine occupational market both pre- and post-automation. As we show in Appendix A.7, their ratio of post- to pre-automation welfare is given by:

$$\Delta_{R^{OLD}\to R^{NEW}} = \frac{P_R^{NEW}}{P_R^{OLD}},$$

In other words, 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 equivalent) welfare.

Welfare change derivations for those who switch occupations or labor force status result in the simple expressions that follow (details are provided in Appendix A.7). First, the welfare change due to automation for those who switched form R to NRM is given by

$$\Delta_{R^{OLD}\to NRM^{NEW}} = \frac{f_{NRM} P_{NRM}^{NEW} E\left(\varepsilon_{NRM}\right)^{R^{OLD}\to NRM^{NEW}}}{f_R P_R^{OLD} E\left(\varepsilon_R\right)^{R^{OLD}\to NRM^{NEW}}}$$

where where $E(\varepsilon_R)^{R^{OLD}\to NRM^{NEW}}$ denotes the average ability In R of those who switch from R to NRM, and equivalently $E(\varepsilon_{NRM})^{R^{OLD}\to NRM^{NEW}}$ denotes the average ability In NRM of those who switch from R to NRM.

Finally, the average change in welfare for R workers who leave the labor force is given by

$$\Delta_{R^{OLD}\to NLF^{NEW}} = \frac{\varepsilon_R^{*,R^{OLD}}}{E\left(\varepsilon_R\right)^{R^{OLD}\to NLF^{NEW}}}$$

Similar expression holds for labor force participants in the NRM occupation and for those out of the labor force participants who enter into the labor force (either in the R or NRM occupation). These closed form solutions, described in Appendix A.7, greatly simplify the calculation of welfare and how it change across steady states.

5. Calibration

In this section we calibrate the model economy, which targets, in general, pre-automation moments. Based on this calibration we evaluate below the impact of different policies in the face of advancing automation technology. This section begins with a discussion of model parameterization. Table 1 lists the various parameters and their values.

Table 1: Calibration

Parameter	Value	Target
Ability Distribution		
μ_{NRM}	1	Normalization
μ_R	1	
σ_{NRM}	0.9803	Occupations allocations and variance of observed wages
σ_R	0.7436	
$\rho_{R,NRM}$	0	See text for details
Preferences		
β	0.9957	Monthly frequency; $r_{annual} = 0.05$
σ	1	log utility
Labor Frisch Elasticity (NRC)	0.5	Chetty et al. (2013)
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_{NNRC}	0.5	Maximum allowed, US 1989
b_o	.0813	Marginal worker indifferent between NLF and unemployment
T_{NRM}	0.137	Average group tax rates
T_R	0.137	
T_{NRC}	0.267	
Depreciation Rates		
δ_K	0.0051	see Eden and Gaggl (2018)
δ_A	0.0174	
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 and Elasticities		
η	.1099	Labor share, Routine Labor Share, ICT capital Income share, 1989; and consistency restriction (see Equation 8)
α	0.8154	
f_R	0.3022	
τ	0.98	
γ	0.31	Physical capital income share (see Eden and Gaggl (2018))
ν	0.46	Split of R workers between NLF and NRM and $\Delta\frac{X_A}{\phi_A}$
ς_1	-1.1	

Ability distribution We assume the work ability distribution, $\Gamma(\varepsilon_R, \varepsilon_{NRM})$, 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, σ_{NRM} (μ_{NRM}) be the standard deviation (mean) of the NRM ability, and $\rho_{\varepsilon_R,\varepsilon_{NRM}}$ 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, $\rho_{\varepsilon_R,\varepsilon_{NRM}}$. Quantitatively, all of the results that we present here and in the policy experiments are virtually identical for different values of ρ. As such we proceed with a benchmark value of $\rho_{\varepsilon_R,\varepsilon_{NRM}} = 0$ and present robustness results in Appendix A.8

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).

Then, 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:

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

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

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

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

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

Since that D is a constant, this results in a truncated bivariate log normal variance:

$$\mathrm{Var}\left(\log \varepsilon_R | \log \varepsilon_R > \log \varepsilon_R^*\right),$$

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 standard deviation of the log observed wages for Routine workers in the data in 1989 is 0.487, while that for NRM equals 0.492).

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 assume CRRA flow utility $\frac{C^{1-\sigma}}{1-\sigma}$, and 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 vacancy cost parameter, κ_0 such that the resulting employment rate across the low-skill workers matches the evidence in Table A4 of 0.95; this implies a monthly job finding rate of 0.38 in all markets in the steady state. The calibration of τ, the bargaining power of the worker, is detailed below with the discussion of the production function parameters.

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 $(\varepsilon_R^*, \varepsilon_{NRM}^*)$ 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. These tax rates are based on the estimates in the Congressional Budget Office distribution of household income in 2015. [17]

Relative prices of automation capital Our measure of advances in automation technology is how much the relative price of automation capital fell between 1989 and 2017 (or, equivalently, the increased productivity in transforming final goods into automation capital, $1/\phi_A$). Given our quantitative goal, we need to focus on a tangible measure of automation and its technological progress. In the literature there are two strands:

[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]At each calculation of a steady state equilibrium (before and after the decline in automation capital price) we allow the profit tax rate, T_π, to adjust such that it balances the government budget constraint. Since investment is fully deducted in the model, this change has no effect on the economy. For all policy experiments we keep this tax rate constant and balance the budget with distortionary labor taxation on the NRC group.

one that concentrates on information-and-communication-technology (ICT) capital, which 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)).The second focuses on robotics (see Graetz and Michaels (2018)).

What has happened to the relative prices of both of these series? With respect to ICT capital, the ICT price, over our period of interest and based on the estimate in in Eden and Gaggl (2018) fell to $\phi_A^{2017} = 0.3244\phi_A^{1989}$.[18] Interestingly, similar magnitudes are seen in the changes of robot pricing. Specifically, Graetz and Michaels (2018) show that the unit price of robots in the US has declined by about 60% between 1990 and 2005 (see their Figure 1). So both measures suggest a similar degree in the change of automation capital.

The specific parameters of the production function we use below are based on the ICT data because, to carry out our quantitative exercise, we need to calibrate (i) automation capital depreciation rates, and (ii) production function parameters to match income shares. This data is available for ICT data, but to the best of our knowledge, is non-existent for Robotics. Finally, based on Eden and Gaggl (2018), we set the relative price of non-automation physical capital to $\phi_K = 1$.

Depreciation rates We use the specific annual capital depreciation rates estimated by Eden and Gaggl (2018). They imply a monthly depreciation rate of $\delta_A = 1.74\%$ for automation capital, and $\delta_K = 0.51\%$ on non-automation capital.

Production function parameters Sspecifications suggested in the polarization empirical literature, such as Autor, Levy and Murnane (2003) and Autor and Dorn (2013), and in the recent optimal robot's tax policy analysis as in Guerreiro, Rebelo and Telels (2019), form the basis of our assumptions that automation capital is a substitute for the R labor input and a relative complement to NRC workers. As such, we assume that (X_A, Y_R) form a composite good, which is then aggregated with the remaining factors.[19] Specifically, we assume aggregate output is produced via

$$Y_t = K_t^{\gamma} Y_{NRM,t}^{\eta(1-\gamma)} \left[(1-\alpha) Y_{NRC,t}^{\varsigma_1} + \alpha \left[X_A^{\nu} + Y_{R,t}^{\nu} \right]^{\frac{\varsigma_1}{\nu}} \right]^{\frac{(1-\eta)(1-\gamma)}{\varsigma_1}} \tag{7}$$

[18] 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.

[19] An alternative CES specification is one where the the composite good is formed between automation capital and NR workers. See for example Krusell et al. (2000) and Eden and Gaggl (2018)

where ν governs the degree of substitution between R labor and automation capital, and ς_1 governs the elasticity of substitution between the (X_A, Y_R) composite and NRC labor. We also assume that aggregate production is Cobb-Douglas with respect to non-automation capital, K. Moreover, Eden and Gaggl (2018) demonstrate that the NRM labor share of national income has not changed during our period of interest. As such, we assume 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 to identify the remaining four parameters are the shares of total labor income, Routine labor income, ICT capital income in GDP, and the fact that, when calibrated to 1989, pre-polarization values, the ratio of ability cutoffs must satisfy:

$$\frac{\varepsilon^*_{NRM}}{\varepsilon^*_R} = \frac{P_R f_R}{P_{NRM} f_{NRM}} \left(\frac{\urcorner_R}{\urcorner_{NRM}} \right)^{\frac{1}{1-\sigma}}, \tag{8}$$

in steady state equilibrium.[20]

The remaining two parameters cannot be identified from first moments in the data: ν, which controls the elasticity of substitution between automation 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 automation capital price fall* and iterate over ν and ς_1 such that we match two moments: (i) the percentage change in in automation capital (i.e. we match the elasticity of automation capital to its relative price), and (ii) our Section 2 result of the 0.63/0.37 split between NLF and NRM in accounting for the decline in R employment propensity among the low-skilled.

6. The welfare impact

What are the welfare implications of advances in automation technology? And what welfare and allocational effects do different policies have? To come to an answer to the first question we calculate the welfare impact of the drop in the relative price of automation capital; in the next section we evaluate different policies.

To quantify the change in consumption equivalent welfare we proceed as follows: we first simulate a billion low-skill individuals, drawing abilities from the calibrated joint log normal distribution. Given the post-automation equilibrium cutoffs for $\varepsilon_R^{*,NEW}$ and $\varepsilon_{NRM}^{*,NEW}$ we then calculate the new steady state measures of NLF, R, and NRM as:

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

[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.

$$NRM^{NEW} = I\left(log(m^{new}) + log(\varepsilon_R) \leq log(\varepsilon_2)\right) I\left(\varepsilon_{NRM}^{*,NEW} \leq \varepsilon_{NRM}\right)$$

$$R^{NEW} = I\left(log(m^{new}) + log(\varepsilon_R) > log(\varepsilon_2)\right) I\left(\varepsilon_{R}^{*,NEW} \leq \varepsilon_{R}\right)$$

where $I(.)$ is an indicator function and $m^{new} = \frac{\varepsilon_{NR}^{*,NEW}}{\varepsilon_{R}^{*,NEW}}$. 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, as we discuss below, the model, following the automation capital price change, predicts three groups of switchers: (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. Based on the welfare expressions of the different groups in the economy discussed in Section 4.3, we calculate the percentage change in consumption-equivalent welfare due to automation for each group separately.

Impact of automation Before discussing the welfare impact, we find it instructive to consider the effects of the automation capital price drop on the economy as, naturally, they underlie the welfare impact. These results are summarized in Table 2.

Overall, aggregate output increases by slightly more than 10 percent. This output rise masks the distributional consequences of the price decline of automation capital. Specifically, with respect to the magnitude of the fall in R, we find that the model economy reduces the likelihood of the low-skilled working in R by 7.85p.p.[21] This transition away from R into NRM and NLF is fueled by a deterioration in the relative return for working as R. Specifically, the model generates a 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}.[22] Overall, the fall in "quantities" (fall in likelihood of working in R) coupled with the decline in "prices" (wages), results, as in the data, in the share of GDP accruing to R declining, while the share of income accruing to NRC labor increases by more than double the drop in aggregate labor.[23]

[21] As discussed in Section 2, and shown in Tables A4 - A5, unconditionally, the fall in the likelihood was 16 p.p. between 1989 and 2017. Thus, the model, when driven by the ICT price change, accounts for about half of this fall.

[22] These efficiency measures, of course, are not the empirically observed measures. As such, using the equilibrium efficiency wages, cutoffs, and employment rates, we construct the average wages (conditional on working in the economy), $E(\omega_R)$, and $E(\omega_{NRM})$. Indeed 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. 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.

[23] Similar patterns are observed in the empirical analysis in Eden and Gaggl (2018).

Table 2: Model Performance

	Data	Model
Employment		
% change in routine share (out of N-NRC)	-16	-7.85
Income Shares (% of GDP)		
p.p. change: Total	-4.30	-2.39
p.p. change: Routine	-9.51	-6.00
p.p. change: Non-Routine Cognitive	4.17	3.50
Wages		
% change in avg. wage gap: Routine/Non-Routine-Manual	-10.00	-3.60

Notes: All changes are between 1989 and 2017; see Eden and Gaggl (2018) for income shares by occupation.

Welfare of previously routine workers There are three groups of interest among individuals who previously labored as R workers: those who remain working in R and those who switch out of R to either NLF or NRM. The bottom panel of Column 1 in Table 3 reports the welfare effects of these three different groups in response to the decline in the price of automation capital.

First, recall from the discussion in Section 4.3 that for those who remain working in R, the change in welfare is exactly the change in prices that final-good producers pay for routine labor input; these prices are translated 1-to-1 to routine worker wages, their consumption, and (consumption-equivalent) welfare. These workers who remain in R suffer a 6.5% drop in welfare (see bottom panel of Column 1, Table 3).

How does the welfare of those who switch occupations or labor force status change? Some R workers have relatively high NRM abilities; post-automation, they switch into NRM (as opposed to remaining R or leaving the labor force). Yet these workers experience an average decline in welfare as well (though less of one than those who remain R); it amounts to 1% in consumption-equivalent terms. Other formerly R have relatively low NRM ability. After the return to R employment drops, they choose to exit the labor force. This group suffers an average welfare deterioration of 4% as reported in the bottom panel of Column 1, Table 3.

All other workers Since NRM labor input complements automation capital, the return to working (and searching) in that occupation rises. In the new steady state, all those previously in NRM choose to stay in it. Welfare increases by 5% for the average NRM remainer.

For most low-skill individuals out of the labor force, the automation capital price decline does not affect their participation choice. Since government transfers, b_o, are unchanged, their welfare is as well. But those with sufficiently high NRM ability respond to the higher return to NRM labor by switching to and participating in the NRM occupational market. The average welfare of this group goes up 3.2%.

Finally, high-skill workers benefit the most from the advances of automation technology. Their consumption-equivalent welfare improves by 22%. This is not surprising since NRC labor input complements automation capital in production and since they are the "capitalists" who hold all firm equity in the economy.

7. Policy experiments

Having ascertained that automation produces an important quantitative welfare impact, we use our model economy as a laboratory to consider a variety of government policy responses to it and their consequences for equilibrium allocations and welfare.

We consider two sets of policies. First, we study the effects of a retraining program aimed at improving the work ability (in a distributional sense) of the low-skilled. Second, we look at 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.[24]

7.1. 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), which captures the idea of training low-skill workers to do non-routine manual work.[25] In this retraining policy, we target those who are out of the labor force (i.e. whose ability below both cutoffs $\varepsilon_R^{*,NEW}$ and $\varepsilon_{NRM}^{*,NEW}$) in the 2017, post-automation steady state.[26]

[24] Before proceeding, 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 automation capital, τ_A. Increasing τ_A to exactly offset the fall in ϕ_A, leaving the effective automation price unchanged, would return the economy to its pre-automation steady state values.

[25] 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

[26] 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.

Table 3: Policy Experiments

		Automation Capital Change	Retraining	UI	UBI	NLF Benefits	Taxation
	Cutoffs						
1)	$\Delta\varepsilon_R^*$	6.70	-0.22	-3.95	10.77	26.37	-9.66
2)	$\Delta\varepsilon_{NRM}^*$	-4.84	4.00	-4.51	9.45	26.66	-10.24
	Labor states						
3)	Φ NLF	2.19	-2.21	-2.20	5.84	15.12	-5.18
4)	Φ R	-3.82	0.27	1.57	-4.69	-11.52	3.81
5)	Φ NRM	1.64	1.94	0.64	-1.15	-3.60	1.37
6)	Emp. Rate R	0.95	0.95	0.945	0.946	0.95	0.95
7)	Emp. Rate NRM	0.95	0.95	0.945	0.946	0.95	0.95
8)	ΔY_{NRC}	1.23	0.37	0.13	-13.87	-8.03	-2.06
9)	ΔY_R	-3.72	0.60	-0.11	-5.03	-12.37	3.13
10)	ΔY_{NRM}	7.14	5.02	-0.75	-4.01	-13.18	3.90
11)	Δ **GDP**	11.98	1.02	-0.06	-10.42	-10.04	0.29
12)	Φ **NRC labor tax**	0.00	-1.51	-0.50	35.19	25.00	9.98
	Wages						
13)	$\Delta\omega_R$	-6.70	0.22	0.14	-7.22	3.42	-4.19
14)	$\Delta\omega_{NRM}$	4.84	-4.00	0.70	-5.90	3.14	-3.61
15)	$\Delta\omega_{NRC}$	23.24	0.83	-0.30	7.50	-3.79	4.45
16)	$\Delta\omega_{NRC}$: after tax	23.24	0.85	0.11	-12.80	-10.64	-2.82
Welfare: Consumption Equivalence							
17)	$\Delta : R^{Old} \to \Delta R^{New}$	-6.48	1.23	1.75	6.23	3.48	10.13
18)	$\Delta : R^{Old} \to \Delta NRM^{New}$	-0.95	NA	2.56	11.69	NA	10.45
19)	$\Delta : R^{Old} \to \Delta NLF^{New}$	-4.01	NA	NA	26.25	16.69	NA
20)	$\Delta : NRM^{Old} \to \Delta R^{New}$	NA	-1.17	NA	NA	3.33	NA
21)	$\Delta : NRM^{Old} \to \Delta NRM^{New}$	4.96	-3.25	2.43	7.43	3.18	10.78
22)	$\Delta : NRM^{Old} \to \Delta NLF^{New}$	NA	-1.99	NA	27.12	16.64	NA
23)	$\Delta : NLF^{Old} \to \Delta R^{New}$	NA	0.00	2.24	NA	NA	5.79
24)	$\Delta : NLF^{Old} \to \Delta NRM^{New}$	3.17	9.23	2.51	NA	NA	6.09
25)	$\Delta : NLF^{Old} \to \Delta NLF^{New}$	0.00	0.00	0.00	34.05	34.71	0.00
26)	$\Delta : NRC^{Old} \to \Delta NRC^{New}$	22.64	1.98	0.07	-21.89	-22.99	-4.98

Notes: (i) Φ denotes percentage point change; (ii) Δ denotes percentage change; (iii) the reference point for the first column is the steady state *beofre* the automation capital price decline; (iv) the reference point for columns 2-6 is the steady state *after* the automation capital price decline.

Starting from the post-automation steady state (described in Column 1 of Table 3), 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. We find that, to prod 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 entices about 10% of non-participants to select into treatment.[27]

This experiment increases GDP by slightly more than 1%, via two effects. First, since labor force participation and NRM ability both rise (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 automation capital, the return to investment increases, leading to jumps in both types of capital stock and adding to output growth.

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

With respect to the low-skill, those *already* working in NRM prior to the experiment see a deterioration in their welfare. A displacement effect is responsible: the increase in the supply of NRM abilities lowers the efficiency price of their labor and leads to an exit from the labor force of workers with NRM abilities near the pre-retraining threshold.[28] Still others are induced to switch to the R occupation. The most ill-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 were working in R prior to retraining observe 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

[27]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.

[28]Note that this experiment treated roughly ten percent of the NLF, which is about 3 percent of the population. Yet NLF went down by only 2.2 p.p. Thus, there is an inflow into the NLF from the NRM due to the displacement effect of about 0.8 p.p.

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) and resulted in an output increase 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 about one-third of per capita GDP, the retraining program has a positive return from an aggregate perspective.

7.2. Redistributive transfers

In this subsection we consider four redistributive policies that transfer resources from high-wage workers (who, as discussed above, in the context of our model, significantly benefit from automation) to middle- and low-wage workers. The four policies are: (i) unemployment insurance (UI) system reform; (ii) the introduction of a universal basic income (UBI); (iii) increased transfers to those outside the labor force; and (iv) changes in the labor taxes levied on the low-skilled.

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

7.2.1. Unemployment insurance benefits

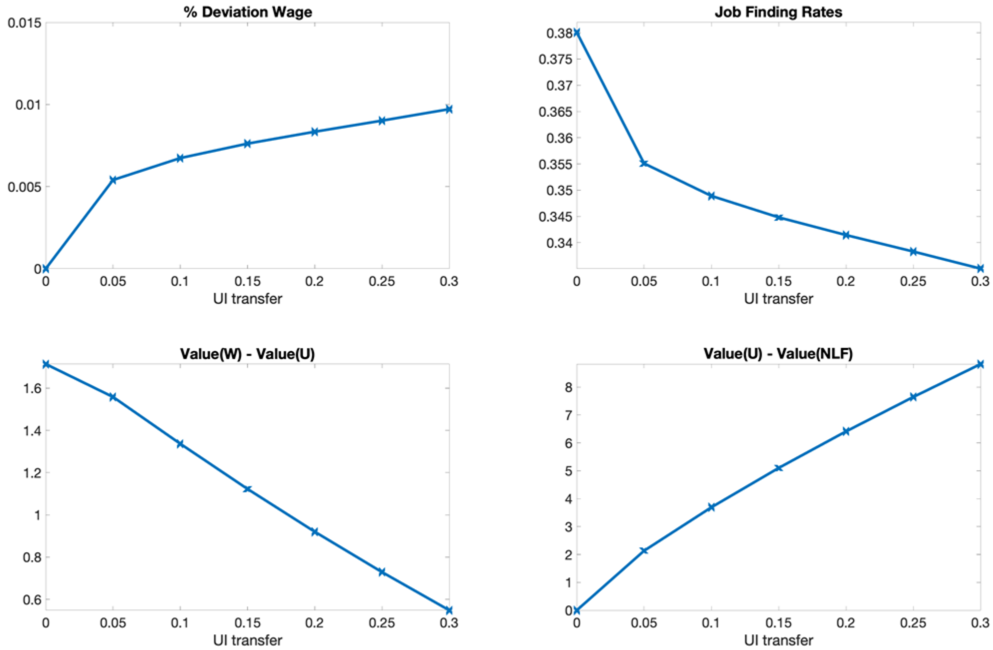
We begin with a change to the UI, with workers receiving an additional transfer while unemployed. The size of this transfer is calibrated so that, as in the Section 7.1, retraining program, the low-skilled labor force participation rate returns to its 1989, pre-automation level. For comparability, we keep the "dollar value" of transfers per recipient fixed across the four redistributive experiments.[29]

Specifically, 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 modelled 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 $C_{u,\varepsilon_R} = b\omega_{\varepsilon_R} + UI$. [30]

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

[30] This additive term in the budget constraint (present also in the UBI analysis below) means that 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) the equilibrium cutoffs are no longer linear functions of ability. Solving for the equilibrium requires additional numerical computation (e.g., numerical integration, spline approximation). 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. Each line in the four different panels shows the response to changes in UI in a simple version of the model with no heterogeneity in production, no taxes, and no curvature in production. The % deviation in wages in the top-left panels are vis-a-vis the wage prior to the introduction of the increased UI benefits.

An illustrative simplified model What is the effect of increased unemployment benefits on the economy? Before discussing it within the context of our GE model, we find it useful to consider the impact such a policy change has within a simplified search-and-matching model with CRRA preferences, though one without: (i) heterogeneity in production; (ii) taxes; and (iii) curvature in production (i.e., a constant productivity in production). Specifically, we consider an individual who, prior to any UI policy change, is indifferent about being unemployed or being outside the labor force (i.e. the individual with $\varepsilon_R = \varepsilon_R^*$). This simplified model will help us emphasize the role of search frictions in driving the effect of the policy change on wages, unemployment, and the labor participation decision. Figure 1 depicts the key outcomes of this simplified model.

Given concavity in preferences, a more generous UI system reduces the difference in utility between being employed and unemployed (see bottom left panel of Figure 1), a key object in the Nash bargaining problem. As a result, the bargained wage increases as the top left panel depicts.[31] Since the worker's productivity does not change, this increase in the wage must lower, via the free entry condition, in a fall in vacancy creation, and in the tightness ratio, which manifests itself in a fall in the job finding rate in the top right panel. Taken together, as the lower right panel depicts, the value of unemployment increase vs. the value of non-participation (which is unaffected by change in the UI system). Hence, a more generous UI system increases the value of participating in the labor force.

The full GE model What are the effects in our full GE model? The third column in Table 3 reports the results of a more generous UI system within our full model economy.

First, as discussed above, the increase in UI benefits increases the value of being unemployed, while the value of being outside the labor force is not affected. This leads to an increase in the value of participating in the labor force as can be seen in the third row.[32]

While labor force participation increases, as in the simplified model above, the increase in UI benefits affects the wage and job finding rates. Hence, 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 posting by firms. To discipline our analysis we require the model to match the elasticity of unemployment duration to unemployment benefits (see Appendix A.9 for a discussion).

Figure 2 depicts the heterogeneous equilibrium effects on the wage and on the job finding rate of the more generous UI policy in our full GE model. The left panel displays the ratio of the new post-policy wage to the pre-policy (and post-automation) wage, for each routine ability level, ε_R. As discussed above in the simplified version of the economy, the increase in the UI transfer leads to an increase in the wage. Figure 2 suggests that 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 and has a bigger effect on the bargaining problem.

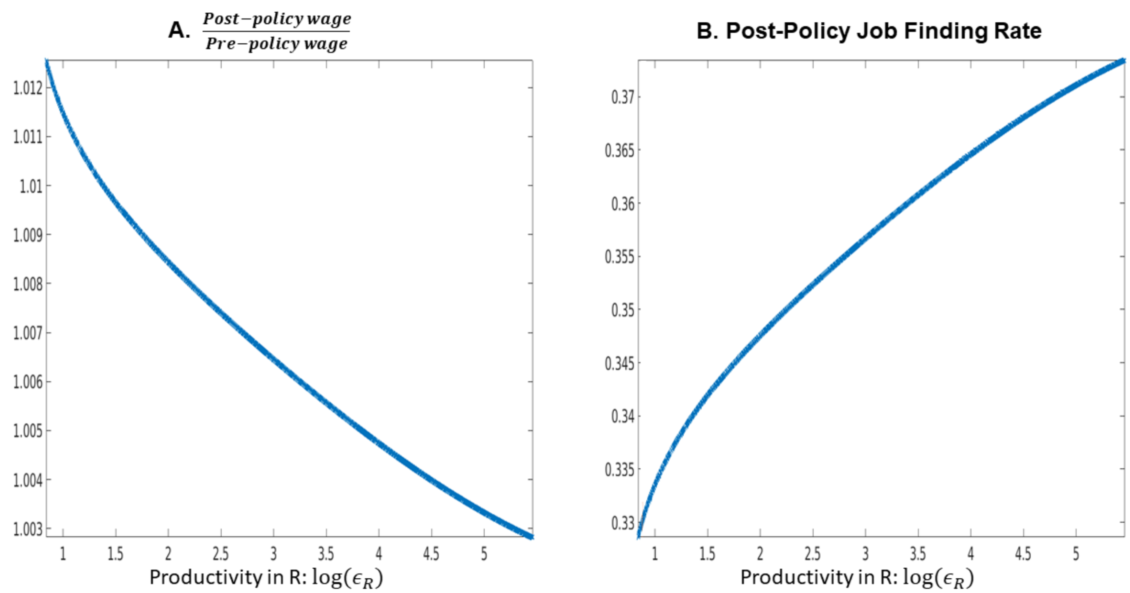
The wage increase reduces the job finding rate as shown in the right panel of Figure 2. For reference, the job finding rate was 0.38 at each ability level prior to the policy change. This decline in the job finding rate manifests itself as a higher unemployment rate, more so at lower ability levels.

Overall, as row 11 in Table 3 reports, the introduction of the UI policy leaves aggregate output essentially unchanged (it falls by less than one-tenth of one percent), despite the increased labor force participation,

[31] The effect discussed here will also naturally be present in models with linear utility.

[32] Quantitatively, we look for the value of the UI transfer that leads the labor force participation of the low-skilled 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 the rest of the transfer experiments below, is equivalent to about 420 dollars per month in 2017.

Figure 2: UI policy: Effects on the relative wage and job finding rates



Notes: The x-axis for both panels is $\log(\varepsilon_R)$. The support includes productivity to the right of the ε_R^* cutoff

since the unemployment rate also rises. That is, the greater generosity of the UI program implies that, conditional on participating in the labor force, there is a drop in the employment rate (see sixth and seventh row in Table 3). So the change in the job-finding rate due to higher UI essentially offsets the rise in labor force participation, leading overall to a minuscule fall in the supply of R and NRM labor input (observable in the ninth and 10th rows). The reduced labor tax levied on NRC workers (see the 12th row and below for a discussion) slightly boosts their labor input (eighth row) and results, overall, in output essentially remaining the same.

In terms of welfare, the UI policy has relatively modest effects, at least relative to the other experiments reported in Table 3. 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 as can be seen in rows 17-25.

Interestingly, as row 26 details, high-skill workers see essentially no change in their welfare: it rises 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 after-tax wages of the high-skilled are almost 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. Moreover, at this level, the majority of low-skilled workers enjoy an increase in welfare only about half as great as the welfare loss they experienced due to the automation capital price drop.[33]

7.2.2. Universal basic income

Our next experiment introduces a universal basic income transfer program. We model the UBI as an identical lump sum transfer, $UBI > 0$, to each individual, irrespective of her skill or labor force status. To make the 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 $C_{e,\varepsilon_R} = \omega_{\varepsilon_R}(1-T_R)+UBI$.[34]

The UBI program reduces GDP by over 10 percent (fourth column of Table 3) as labor force participation, the employment of low-skilled workers, and the labor input of high-skilled workers decline. What explains such a difference relative to the previous UI case? The UBI program (see below), because of its budgetary implications, requires a steep increase in the labor tax rate of the NRC group. This increase lowers the supply of hours they work, which alters the return to labor force participation for low-skilled workers in the economy.

An illustrative simplified model Again, using a simplified model is helpful in disentangling the channels through which the policy affects the economy. Figure 3 depicts the results from two simplified models.

First, consider the simplified model used in the UI policy example, referred to as Equilibrium/DMP in Figure 3. Under it, individuals receive a transfer not conditional on their employment state. This induces a change in the value of employment, of non-participation, and of being unemployed. Due to the concavity of preferences, the difference between being unemployed and employed falls, as in the UI case (bottom left panel). This strengthens the worker's bargaining position and results both in an increased bargained wage (upper left panel) and in a reduced job-finding rate (upper right panel). Overall, this increase in the value of unemployment increases the value of participation. However, in contrast to the UI case, the value of non-participation in the case of UBI climbs at the same time. Which force dominates? The bottom right panel of Figure 3 shows that, in this Equilibrium/DMP case, the value of unemployment minus the value of non-participation goes up, implying that the DMP forces would be fuelling an *increase* in participation.

However, the UBI transfers to everyone in the economy naturally need to be financed. As evident in

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

[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 7.2.1. Moreover, this policy experiments adds a new expenditure term to the government budget constraint, eq. 4.

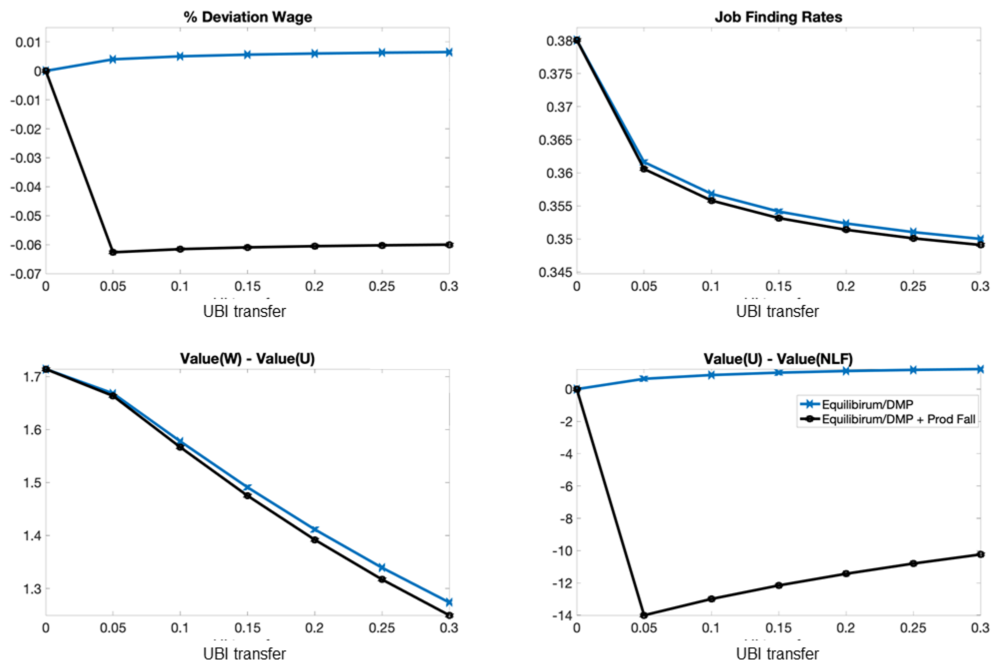
our full model below, this financing requirement profoundly increases the distortionary taxation NRC workers face and causes their labor input to decline. Because NRC workers are complements to R and NRM workers, the plunge in the NRC labor input causes the wages of R and NRM workers to fall. To mimic this drop in productivity (shown below in our full model economy) in this simplified version, we repeat the Equilibrium/DMP exercise with a single change: we feed in a decrease in worker productivity that matches the percentage decline in R productivity from our full GE model economy (about 6 percent), depicted as the "Equilibrium/DMP + Prod Fall" in Figure 3. In this case, the wage drop is enough to overturn the results discussed above, and the value of non-participation increases vis-Ã¡-vis the value of being unemployed (and participating). This discussion highlights the importance of analyzing the effects of UBI within a GE model with government budget constraints. Without considering the budgetary needs of financing the UBI program, its introduction would have increased labor force participation.

The full GE model The overall effects in our full model economy are presented in the fourth column in Table 3. The relative values of being unemployed or outside the labor force mentioned above are reflected in the ability cutoffs for participation in the labor force rising(first two rows in Table 3). As discussed above, all else equal, even though workers receive the UBI *both* when they are unemployed and employed, the curvature in the utility implies that, conditional on labor force participation, the increase in the value of unemployment versus employment improves the worker's outside option in the Nash bargaining: wages rise, job creation falls, and unemployment goes up (as in the previous UI experiment).

However, as rows 13-14 in Table 3 indicate, 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 p.p. in order to fund the UBI payment (see row 12). This leads to an obvious fall in NRC labor input of about 13% as the eighth row report. 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-skilled labor. As in the simplified model discussion above, this reduces the value of labor force participation being reflected in the increase in NLF as reported in the third row.

Figure 4 illusrates the effects on the wage and job-finding rate of a more generous UBI system within our full model economy. The left panel details the ratio of the new equilibrium wage to the pre-UBI one for each routine ability level, ε_R. Post-UBI, the wage declines for each ability, by about 6 to 7 percent, less for the lower ability. The productivity drop of R workers due to the supply decline of NRC workers is common to all R workers (and similar for NRM workers). But for lower ability (and low-skill) workers, the UBI

Figure 3: UBI policy



Notes: The x-axis depicts different UBI transfers; a value of 0.3 matches the ratio of the UBI transfer to the wage of the marginal Routine worker in our economy prior to the introduction of the program. The Equilibrium/DMP line shows the response to changes in UBI in a simple version of the model with no heterogeneity in production, no taxes, and no curvature in production. The Equilibrium/DMP+Prod Fall is similar to the Equilibrium/DMP model, but where we feed a fall in the worker's productivity that matches the percentage fall in the worker's productivity due to the fall in NRC labor input in our full model.

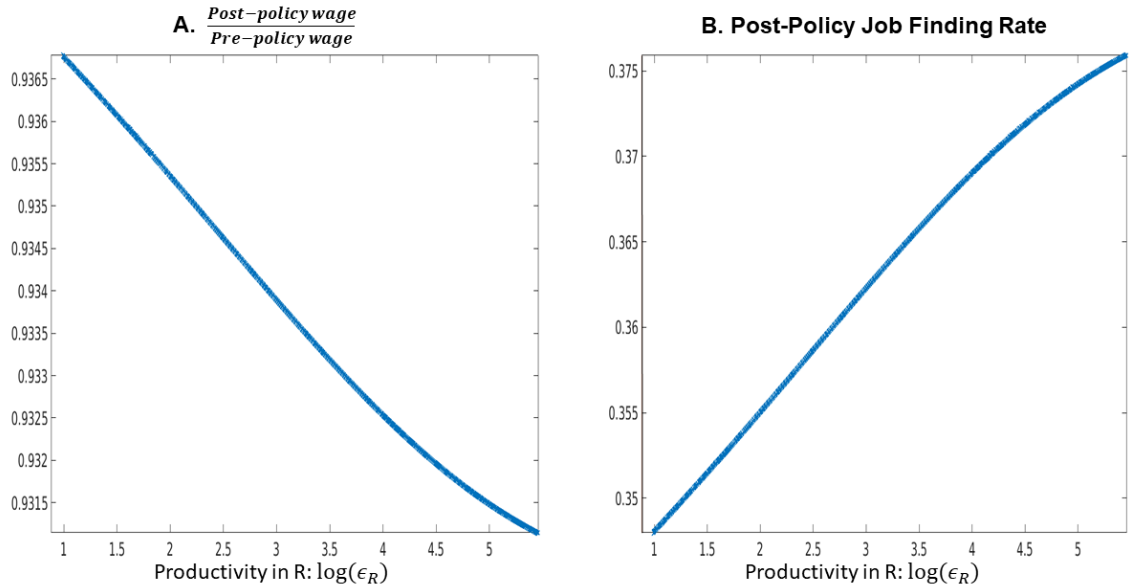
transfer amounts to a bigger fraction of income and thus strengthens their bargaining position more relative to higher ability low-skill workers.

This productivity drop of R workers lowers the job-finding rate (right panel of Figure 4) where we remind the reader that prior to the UBI policy change, the job-finding rate was 0.38 for each ability. Since wages fall relatively more for higher ability low-skill workers, their job-finding rates decline by less relative to lower ability low-skill workers. Overall, this reduction in the job-finding rates for R workers manifests as a higher unemployment rate, more so at the lower ability levels (rows six and seven of Table 3).

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. This effect is several times larger than the effect of automation itself.

In terms of welfare, the UBI program's effects are heterogeneous. Although high-skill workers receive a

Figure 4: UBI policy: Effects on the relative wage and job finding rates



Notes: The x-axis for both figures is $\log(\varepsilon_R)$. The support includes productivity to the right of the ε_R^* cutoff

UBI transfer, it is exceeded by the drop in their after-tax labor income and equity income (as the economy's firm owners). As the last row reveals, they experience a 22% consumption-equivalent loss of welfare, similar in absolute magnitude to their welfare gain due to automation!

By contrast, the low-skilled, especially those who choose to remain in, or transition toward, labor force non-participation, enjoy significant welfare gains. The welfare of even the low-skilled who continue to work improves (although their wages fall) due to the mere fact that the UBI transfer is large enough vis-Ã¡-vis their wage to represent a significant component of their income. Overall, for most unskilled workers, their UBI gains in welfare exceed their losses associated with automation.

7.2.3. Transfers to non-participation

The next policy experiment increases transfers to those not longer participating in the labor force. As before, the increase for each non-participant is the same in dollar terms as previous ones.

Not surprisingly, this program leads to lower labor force participation (fifth column in Table 3); non-participation rises by 15 p.p (see the third row). To finance the program, the distortionary tax rate on high-skill labor increases by 25 p.p (see the 12th row), leading to a fall in NRC labor input (see the eighth row). 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 suffer a major loss in after-tax labor income and equity income. Their welfare falls by 23% (last row). For the low-skilled, the greatest beneficiaries are those who choose labor force non-participation. These individuals enjoy greater welfare, as in the UBI case. For those who remain in the labor force, the exit from it by those of lower ability increases their welfare modestly, via the equilibrium effect on their wages; overall this group's welfare increases by about half of the extent in the UBI case.

7.2.4. Progressivity of taxation

The policy experiments of Sections 7.2.2 and 7.2.3 suggest that there is much room for redistribution. However, such transfer programs come at a dramatic cost, in terms of aggregate output and distortionary welfare losses for high-skill workers. Here, in our last experiment, we explore an alternative way to redistribute resources that involves smaller output and welfare losses for the high-skilled.

Specifically, we consider a more progressive tax system, where 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 7.2.1 through 7.2.3. To accomplish this, the tax rate falls to essentially zero and for simplicity, we set $T_{NRM} = T_R = 0$. Maintaining government budget balance requires an increase in the labor tax rate levied on high-skill workers.

The sixth and final column in Table 3 reports the effect of this policy. First, in equilibrium, as the 12th row reports, this policy requires an increase in the tax rate levied on the high skilled of 10 p.p., which is markedly smaller than those of Sections 7.2.2 and 7.2.3.

Eliminating income taxation on low-skill workers naturally increases their value of participation, resulting in an approximately 5 p.p increase in their labor force participation. By contrast, the tax increase on the high-skilled reduces their labor supply (eighth row), but by less than in the cases of the UBI and transfers to the NLF policies. These offsetting changes in employment and labor supply are reflected in the pre-tax wage rates earned in R, NRM, and NRC occupations. They also imply that there is essentially no impact on aggregate output.

Overall, the increase in the supply of low-skilled and the decrease in the supply of high-skilled labor reduces low-skilled wages (rows 13 and 14). But the *after tax* wages of the low-skilled skilled go up by about 10 percent.

This rise in after-tax wages implies that, in terms of welfare, this policy experiment delivers similar welfare gains to the low-skilled who participate in the labor market as the UBI experiment does. But the gains are not reaped disproportionately by those out of the labor force (who see no increase in their welfare in this tax reform case). Making taxation more progressive favors those who remain in, and elect to join, the labor force, and increases labor force participation. Finally, this experiment also results in much smaller welfare losses for the high-skilled relative to the UBI or increasing transfers to non-participants policies.

7.2.5. Summary and program comparison

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

A policy that makes UI benefits more generous 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 for all. Most low-skilled workers enjoy an increase in welfare equal to about half of the welfare loss they suffered due to the decline in the automation capital price.

By contrast, the introduction of a UBI or an increase in the generosity of transfers to labor force non-participants reduce labor force participation, labor supply, and aggregate income. Moreover, while increasing welfare to the low-skilled (in the UBI case this welfare increase is bigger in absolute value than the welfare loss due to automation), they impose large welfare costs to the high-skilled.

Finally, making the tax system more progressive has strong redistributive effects, raises labor force participation, has little impact on aggregate income, and imposes relatively small welfare losses on the high-skilled. The low-skilled who remain in the labor force enjoy an increase in their welfare greater than the loss they experienced due to the fall in automation capital prices.

8. 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. We develop a heterogeneous agent macroeconomic model with investment in automation capital, labor force participation and occupational choice, and government policy. 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 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.

References

Abel, Andrew. 2007. "Optimal Capital Income Taxation." *NBER Working paper 13354*.

Acemoglu, Daron, and David Autor. 2011. "Skills, tasks and technologies: Implications for employment and earnings." In *Handbook of labor economics*. Vol. 4, 1043–1171. Elsevier.

Acemoglu, Daron, and Pascual Restrepo. 2019. "Robots and Jobs: Evidence from US Labor Markets." *Journal of Political Economy*.

Altonji, Joseph G, Prashant Bharadwaj, and Fabian Lange. 2012. "Changes in the characteristics of American youth: Implications for adult outcomes." *Journal of Labor Economics*, 30(4): 783–828.

Atalay, Enghin, Phai Phongthiengtham, Sebastian Sotelo, and Daniel Tannenbaum. 2018. "New technologies and the labor market." *Journal of Monetary Economics*, 97: 48–67.

Autor, David H., and David Dorn. 2013. "The growth of low-skill service jobs and the polarization of the US labor market." *American Economic Review*, 103(5): 1553–97.

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

Autor, David H., Lawrence F. Katz, and Melissa S. Kearney. 2006. "The Polarization of the U.S. Labor Market." *American Economic Review*, 96(2): 189–194.

Beaudry, Paul, David A. Green, and Benjamin M. Sand. 2016. "The Great Reversal in the Demand for Skill and Cognitive Tasks." *Journal of Labor Economics*, 34(S1): 199–247.

Card, David, Jochen Kluve, and Andrea Weber. 2018. "What Works? A Meta Analysis of Recent Active Labor Market Program Evaluations." *Journal of the European Economic Association*, 16(3): 894–931.

Chetty, Raj. 2008. "Moral Hazard versus Liquidity and Optimal Unemployment Insurance." *Journal of Political Economy*, 116(2): 173–234.

Chetty, Raj, Adam Guren, Day Manoli, and Andrea Weber. 2013. "Does Indivisible Labor Explain the Difference between Micro and Macro Elasticities? A Meta-Analysis of Extensive Margin Elasticities." *NBER Macroeconomics Annual*, 27: 1–56.

Cortes, Guido Matias, Nir Jaimovich, and Henry E. Siu. 2017. "Disappearing routine jobs: Who, how, and why?" *Journal of Monetary Economic*, 91: 69–87.

Cortes, Guido Matias, Nir Jaimovich, and Henry E. Siu. 2018. "The End of Men and Rise of Women in the High-Skilled Labor Market."

Cortes, Matias. 2016. "Where Have the Middle-Wage Workers Gone? A Study of Polarization using Panel Data." *Journal of Labor Economics*, 34(1): 63–105.

Diamond, Peter A. 1982. "Wage determination and efficiency in search equilibrium." *The Review of Economic Studies*, 49(2): 217–227.

Eden, Maya, and Paul Gaggl. 2018. "On the Welfare Implications of Automation." *Review of Economic and Dynamics*, 29: 15–43.

Gaggl, Paul, and Greg C. Wright. 2017. "A Short-Run View of What Computers Do: Evidence from a U.K. Tax Incentive A Short-Run View of What Computers Do: Evidence from a U.K. Tax Incentive." *American Economic Journal: Applied Economics*, 9(3): 262–294.

Goos, Maarten, Alan Manning, and Anna Salomons. 2009. "Job Polarization in Europe." *American Economic Review*, 99(2): 58–63.

Goos, Maarten, and Alan Manning. 2007. "Lousy and Lovely Jobs: The Rising Polarization of Work in Britain." *The Review of Economics and Statistics*, 89(1): 118–133.

Graetz, Georg, and Guy Michaels. 2018. "Robots at work." *Review of Economics and Statistics*, 100(5): 753–768.

Guerreiro, Joao, Sergio Rebelo, and Pedro Telels. 2019. "Should Robots be Taxed?"

Jaimovich, Nir, and Henry E Siu. 2012. "The trend is the cycle: Job polarization and jobless recoveries." National Bureau of Economic Research.

Krusell, Per, Lee E. Ohanian, JosÈ-Victor RÌos-Rull, and Giovanni L. Violante. 2000. "Capital-Skill Complementarity and Inequality: A Macroeconomic Analysis." *Econometrica*, 68(5): 1029–1054.

Meyer, Bruce D. 1990. "Unemployment Insurance and Unemployment Spells." *Econometrica*, 58(4): 757–782.

Michaels, Guy, Ashwini Natraj, and John Van Reenen. 2014. "Has ICT polarized skill demand? Evidence from eleven countries over 25 years." *Review of Economics and Statistics*, 96(1): 60–77.

Mortensen, Dale T. 1982. "The matching process as a noncooperative bargaining game." In *The economics of information and uncertainty*. 233–258. University of Chicago Press.

Pissarides, Christopher A. 1985. "Short-Run Equilibrium Dynamics of Unemployment, Vacancies, and Real Wages." *The American Economic Review*, 75(4): 676–690.

Pissarides, Christopher A., and Barbara Petrongolo. 2001. "Looking into the Black Box: A Survey of the Matching Function." *Journal of Economic Literature*, 39(2): 390–431.

Tuzel, Selale, and Miao Ben Zhang. 2019. "Economic Stimulus at the Expense of Routine- Task Jobs." *Working Paper*.

vom Lehn, Christian. 2019. "Labor market polarization, the decline of routine work, and technological change: A quantitative analysis." *Journal of Monetary Economics*.

Yedid-Levi, Yaniv. 2016. "Why does employment in all major sectors move together over the business cycle?" *Review of Economic Dynamics*, 22: 131–156.

A. Appendix

A.1. Occupation classification

We adopt the occupational classification system used in Jaimovich and Siu (2012) that affords ease of data access and replication. The classification is based on the categorization of occupations in the 2000 Standard Occupational Classification system. Non-routine cognitive workers are those employed in "management, business, and financial operations occupations" and "professional and related occupations". Routine cognitive workers are those in "sales and related occupations" and "office and administrative support occupations". Routine manual occupations are "production occupations", "transportation and material moving occupations", "construction and extraction occupations", and "installation, maintenance, and repair occupations". Non-routine manual occupations are "service occupations". Detailed information on 3-digit occupational codes are available from the authors upon request.

A.2. Machine learning details

A.2.1. Classification errors

Our ML approach classifies each person (at each point in time) into one of the four "likely" occupational groups (NRC, RC, NRM, and RM). However we present our main results aggregating to two workers types – NRC and non-NRC, hence Tables A1 and A2 show the confusion matrices for those two categories, separately for men and women respectively. In each matrix we add the precision (share of correctly classified objects within a predicted category) and recall (share of observed that were picked up by the prediction within a category) values.

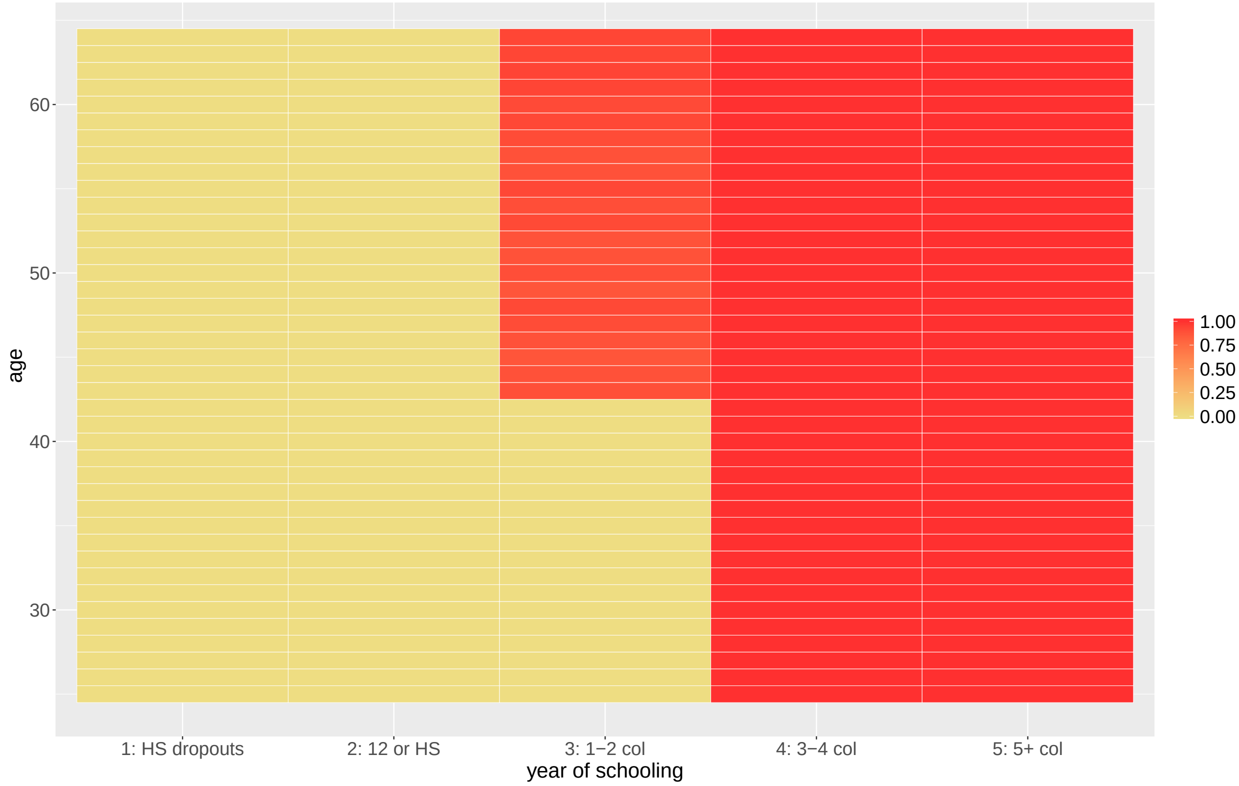
Table A1: Confusion Matrix - Men

		Classified		
		NRC	non-NRC	Precision
True	NRC	506,002	294,252	**63.23%**
	non-NRC	242,256	1,213,131	**83.35%**
	Recall	**67.62%**	**80.48%**	

Table A2: Confusion Matrix - Women

		Classified		
		NRC	non-NRC	Precision
True	NRC	342,362	150,507	**69.46%**
	non-NRC	241,376	1,167,622	**82.87%**
	Recall	**58.65%**	**88.58%**	

Figure A1: Probability of Non-Routine Cognitive by Cell



Notes: The probability of men in a specific education-age cell to be classified as non-NRC by the random forest algorithm.

A.2.2. Recovering true series from series with errors

The classification errors discussed in A.2.1 imply that we do not have "clean" series for the dynamics of NRC and non-NRC type persons. However, we show now that while we cannot recover perfectly correct the classification a the individual level, it is possible to correct the aggregate series of interest. Suppose that we are interested in recovering the share or persons of NRC and non-NRC types in specific labor force status, and call these x_{NRC}, and x_{NNRC}. Define our observed values from the classifier as $\hat{x}_{NRC}$, and $\hat{x}_{NNRC}$, and define the classification outcomes in terms of the following shares (with the convention $S_{True|Classified}$) as in Table A3:

Table A3: Classification Definitions

		Classified	
		NRC	non-NRC
True	NRC	$S_{NRC\|NRC}$	$S_{NRC\|NNRC}$
	non-NRC	$S_{NNRC\|NRC}$	$S_{NNRC\|NNRC}$

We can then write the observed values as a function of the true values and the share as follows

$$\begin{aligned} \hat{x}_{NRC} &= S_{NRC|NRC}x_{NRC} + S_{NNRC|NRC}x_{NNRC} \\ \hat{x}_{NNRC} &= S_{NRC|NNRC}x_{NRC} + S_{NNRC|NNRC}x_{NNRC} \end{aligned}$$

Thus if we know the shares in A3, we are left with a simple two-equation two-unknown linear system that will allow us to recover x_{NRC} and x_{NNRC}. The first way to recover the shares in A3 is to use the classification errors from the training, reported in section A.2.1. The second approach is to use the restrictions implied by nature by some of the series. For example, the series or true values of employment share in R occupations for the NRC type *during the training period*, should be roughly zero. While the second approach is appealing, it can only be applied to the occupation series, and not to the NLF series, for which we apply the first approach. It is important to note that both approaches require the assumption that the classification errors are not correlated with the labor market status and occupation choice in the post-training period.

A.3. Machine Learning: Detailed Results

As discussed in section 2, we use an ML approach to 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 the pre-

Table A4: 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

Notes: The first row of the table reports the share of the population in the non-NRC and NRC groups for men aged 25-64 in 1989 and 2017. Rows 2-6 report the fraction of men in 5 labor market states: 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. The last row reports the unemployment rate. The categorization into non-NRC and NRC groups was done using a random forest algorithm (see text for more details). CPS weights are applied in all calculations.

polarization era, before the rise of automation. In this Appendix we provide the detailed results from this analysis.

Table A4 summarizes our findings. As discussed in the text, 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 p.p. or 16 log point fall. This decline is accounted for by the increase in non-participation and in participation in employment in NRM occupations.

Employment and occupation dynamics for the high-skilled (NRC) 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 A4 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 (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

Table A5: 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

Notes: The first row of the table reports the share of the population in the non-NRC and NRC groups for men aged 25-64 in 1989 and 2017. Rows 2-6 report the fraction of men in 5 labor market states: 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. The last row reports the unemployment rate. The categorization into non-NRC and NRC groups was done using a random forest algorithm (see text for more details). CPS weights are applied in all calculations.

into middle-paying R occupations). This suggests that the changes for the low-skilled are particularly linked to the decline of R occupations.

Employment and occupation dynamics for women Women display similar patterns as those of 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 A5 present the same information as in Table A4 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.[35] 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 A5 show, during 2001–2017 as well.

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

A.4. Classifying workers using cognitive ability measures (AFTQ Scores)

In the last part of Section 2, we discuss an alternative approach to the ML, using cognitive ability measures from the NLSY to classify workers. We provide here more details about this approach. For comparability of scores between the 1979 and 1997 NLSY surveys, we use the standardized measure provided by Altonji, Bharadwaj and Lange (2012). 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, when individuals in this sample are around the age of 30. Given the trends in female participation referred to above, we focus our analysis on men. 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).

Table A6 indicates that, conditional on employment, there are large differences in the propensity to work in non-NRC occupation (i.e 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 A7 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 results from this table are discussed in the text.

Table A6: Share of 1979 NLSY men working in Routine or non-Routine Manual occupations in 1989-1990

	AFQT 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 as measured by the AFQT score. For comparability of scores between the 1979 and 1997 NLSY surveys, we use the standardized measure provided by Altonji, Bharadwaj and Lange (2012)

Table A7: 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.

A.5. Wage function derivations

Taking the first order condition with respect to wages we have

$$\tau\left(\frac{\partial J\left(x_{R,\varepsilon_R},\Lambda\right)}{\partial x_{R,\varepsilon_R}}\right)\left[U'\left(C_{e,R,\varepsilon}\right)\left(1-T_{e,R,\varepsilon}\right)-U'\left(C_{u,R,\varepsilon}\right)\left(1-T_{u,R,\varepsilon}\right)b_{R,\varepsilon}\right]=\left(1-\tau\right)\left(\tilde{V}_{R,\varepsilon}\left(\Lambda\right)\right)\left(1-T_{\pi}\right)$$

or

$$\begin{aligned}\tilde{V}_{R,\varepsilon}\left(\Lambda\right)&=\left[U'\left(C_{e,R,\varepsilon}\right)\left(1-T_{e,R,\varepsilon}\right)-U'\left(C_{u,R,\varepsilon}\right)\left(1-T_{u,R,\varepsilon}\right)b_{R,\varepsilon}\right]\frac{\tau}{1-\tau}\frac{1}{1-T_{\pi}}\frac{\partial J\left(x_{R,\varepsilon_R},\Lambda\right)}{\partial x_{R,\varepsilon_R}}\\&=\xi\frac{\tau}{1-\tau}\frac{1}{1-T_{\pi}}\frac{\partial J\left(x_{R,\varepsilon_R},\Lambda\right)}{\partial x_{R,\varepsilon_R}}\end{aligned}$$

Where $\xi\equiv\left[U'\left(C_{e,R,\varepsilon}\right)\left(1-T_{e,R,\varepsilon}\right)-U'\left(C_{u,R,\varepsilon}\right)\left(1-T_{u,R,\varepsilon}\right)b_{R,\varepsilon}\right]$. Substituting for the marginal value of workers, and using the first order condition one period ahead, we can right the left hand side as

$$\begin{aligned}&\tilde{V}_{R,\varepsilon}\left(\Lambda\right)=U\left(\omega_{R,\varepsilon}\left(1-T_{e,R,\varepsilon}\right)\right)-U\left(b_{R,\varepsilon}\omega_{R,\varepsilon}\left(1-T_{u,R,\varepsilon}\right)\right)+\beta\left(1-\delta-\mu\left(\theta_{R,\varepsilon_R}\right)\right)\tilde{V}_{R,\varepsilon}\left(\Lambda'\right)=\\&=U\left(C_{e,R,\varepsilon}\right)-U\left(C_{u,R,\varepsilon}\right)+\beta\left(1-\delta-\mu\left(\theta_{R,\varepsilon_R}\right)\right)\xi\frac{\tau}{1-\tau}\frac{1}{1-T_{\pi}}\frac{\partial J\left(x_{R,\varepsilon_R},\Lambda\right)}{\partial x_{R,\varepsilon_R}}\end{aligned}$$

Substitute for the marginal value of the firm we can write the right hand side as follows:

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

Therefore we have

$$U\left(C_{e,R,\varepsilon}\right)-U\left(C_{u,R,\varepsilon}\right)+\beta\left(1-\delta-\mu\left(\theta_{R,\varepsilon_R}\right)\right)\xi\frac{\tau}{1-\tau}\frac{1}{1-T_{\pi}}\frac{\partial J\left(x_{R,\varepsilon_R},\Lambda\right)}{\partial x_{R,\varepsilon_R}}=$$
$$\xi\frac{\tau}{1-\tau}\frac{1}{1-T_{\pi}}\left[\left(1-T_{\pi}\right)\left(f_R\varepsilon_R P_R-\omega_{R,\varepsilon_R}\right)+\left(1-\delta\right)\beta\frac{\partial J\left(x_{R,\varepsilon_R},\Lambda\right)}{\partial x_{R,\varepsilon_R}}\right]$$
$$\Rightarrow$$
$$U\left(C_{e,R,\varepsilon}\right)-U\left(C_{u,R,\varepsilon}\right)-\beta\mu\left(\theta_{R,\varepsilon_R}\right)\xi\frac{\tau}{1-\tau}\frac{1}{1-T_{\pi}}\frac{\partial J\left(x_{R,\varepsilon_R},\Lambda\right)}{\partial x_{R,\varepsilon_R}}=$$
$$\xi\frac{\tau}{1-\tau}\left(f_R\varepsilon_R P_R-\omega_{R,\varepsilon_R}\right)$$
$$\Rightarrow$$
$$\frac{1-\tau}{\tau}\frac{1}{\xi}\left(U\left(C_{e,R,\varepsilon}\right)-U\left(C_{u,R,\varepsilon}\right)\right)-\beta\mu\left(\theta_{R,\varepsilon_R}\right)\frac{1}{1-T_{\pi}}\frac{\partial J\left(x_{R,\varepsilon_R},\Lambda\right)}{\partial x_{R,\varepsilon_R}}=$$
$$f_R\varepsilon_R P_R-\omega_{R,\varepsilon_R}$$
$$\Rightarrow$$
$$\omega_{R,\varepsilon_R}=f_R\varepsilon_R P_R-\frac{1-\tau}{\tau}\frac{1}{\xi}\left(U\left(C_{e,R,\varepsilon}\right)-U\left(C_{u,R,\varepsilon}\right)\right)+\beta\theta_{R,\varepsilon_R}q\left(\theta_{R,\varepsilon_R}\right)\frac{1}{1-T_{\pi}}\frac{\partial J\left(x_{R,\varepsilon_R},\Lambda\right)}{\partial x_{R,\varepsilon_R}}$$

where we substitute the relationship $\mu\left(\theta_{R,\varepsilon_R}\right)=\theta_{R,\varepsilon_R}q\left(\theta_{R,\varepsilon_R}\right)$. Finally, we can use the steady state version of the first order condition for vacancies $\left(1-T_{\pi}\right)\kappa_{R,\varepsilon_R}=E\left[\beta q\left(\theta_{R,\varepsilon_R}\right)\frac{\partial J\left(x'_{R,\varepsilon_R},\Lambda'\right)}{\partial x'_{R,\varepsilon_R}}\right]$. This yields the general wage function

$$\omega_{R,\varepsilon_R}=f_R\varepsilon_R P_R-\frac{1-\tau}{\tau}\frac{1}{\xi}\left(U\left(C_{e,R,\varepsilon}\right)-U\left(C_{u,R,\varepsilon}\right)\right)+\theta_{R,\varepsilon_R}\kappa_{R,\varepsilon_R}=$$
$$f_R\varepsilon_R P_R-\frac{1-\tau}{\tau}\frac{U\left(C_{e,R,\varepsilon}\right)-U\left(C_{u,R,\varepsilon}\right)}{U'\left(C_{e,R,\varepsilon}\right)\left(1-T_{e,R,\varepsilon}\right)-U'\left(C_{u,R,\varepsilon}\right)\left(1-T_{u,R,\varepsilon}\right)b_{R,\varepsilon}}+\theta_{R,\varepsilon_R}\kappa_{R,\varepsilon_R}$$

When we assume a CRRA utility function $U\left(C\right)=\frac{C^{1-\sigma}}{1-\sigma}$ and that there are no lump sum transfers to workers who are in the labor force then we can simplify further:

$$
\begin{aligned}
&\frac{U\left(C_{e,R,\varepsilon}\right)-U\left(C_{u,R,\varepsilon}\right)}{U'\left(C_{e,R,\varepsilon}\right)\left(1-T_{e,R,\varepsilon}\right)-U'\left(C_{u,R,\varepsilon}\right)\left(1-T_{u,R,\varepsilon}\right)b_{R,\varepsilon}}=\\
&\frac{\frac{\left(C_{e,R,\varepsilon}\right)^{1-\sigma}}{1-\sigma}-\frac{\left(C_{u,R,\varepsilon}\right)^{1-\sigma}}{1-\sigma}}{\left(C_{e,R,\varepsilon}\right)^{-\sigma}\left(1-T_{e,R,\varepsilon}\right)-\left(C_{e,R,\varepsilon}\right)^{-\sigma}\left(1-T_{u,R,\varepsilon}\right)b_{R,\varepsilon}}=\\
&\frac{1}{1-\sigma}\frac{\left(\omega_{R,\varepsilon_R}\left(1-T_{e,R,\varepsilon}\right)\right)^{1-\sigma}-\left(b_{R,\varepsilon}\omega_{R,\varepsilon_R}\left(1-T_{u,R,\varepsilon}\right)\right)^{1-\sigma}}{\left(\omega_{R,\varepsilon_R}\left(1-T_{e,R,\varepsilon}\right)\right)^{-\sigma}\left(1-T_{e,R,\varepsilon}\right)-\left(b_{R,\varepsilon}\omega_{R,\varepsilon_R}\left(1-T_{u,R,\varepsilon}\right)\right)^{-\sigma}\left(1-T_{u,R,\varepsilon}\right)b_{R,\varepsilon}}=\\
&\frac{1}{1-\sigma}\frac{\left(\omega_{R,\varepsilon_R}\right)^{1-\sigma}\left(1-T_{e,R,\varepsilon}\right)^{1-\sigma}-\left(\omega_{R,\varepsilon_R}\right)^{1-\sigma}\left(1-T_{u,R,\varepsilon}\right)^{1-\sigma}b_{R,\varepsilon}^{1-\sigma}}{\left(\omega_{R,\varepsilon_R}\right)^{-\sigma}\left(1-T_{e,R,\varepsilon}\right)^{1-\sigma}-\left(\omega_{R,\varepsilon_R}\right)^{-\sigma}\left(1-T_{u,R,\varepsilon}\right)^{1-\sigma}b_{R,\varepsilon}^{1-\sigma}}=\\
&\frac{1}{1-\sigma}\frac{\left(\omega_{R,\varepsilon_R}\right)^{1-\sigma}\left[\left(1-T_{e,R,\varepsilon}\right)^{1-\sigma}-\left(1-T_{u,R,\varepsilon}\right)^{1-\sigma}b_{R,\varepsilon}^{1-\sigma}\right]}{\left(\omega_{R,\varepsilon_R}\right)^{-\sigma}\left[\left(1-T_{e,R,\varepsilon}\right)^{1-\sigma}-\left(1-T_{u,R,\varepsilon}\right)^{1-\sigma}b_{R,\varepsilon}^{1-\sigma}\right]}=\\
&\frac{1}{1-\sigma}\omega_{R,\varepsilon_R}
\end{aligned}
$$

and as a result the wage function simplifies to

$$
\begin{aligned}
&\omega_{R,\varepsilon_R}=f_R\varepsilon_R P_R+\theta_{R,\varepsilon_R}\kappa_{R,\varepsilon_R}-\frac{1-\tau}{\tau}\frac{1}{1-\sigma}\omega_{R,\varepsilon_R}\\
&\Rightarrow\\
&\omega_{R,\varepsilon_R}=\frac{1}{1+\frac{1-\tau}{\tau}\frac{1}{1-\sigma}}\left[f_R\varepsilon_R P_R+\theta_{R,\varepsilon_R}\kappa_{R,\varepsilon_R}\right]
\end{aligned}
$$

Armed with this wage function we move to the optimality condition for vacancies

$$
\frac{\kappa_{R,\varepsilon_R}}{q\left(\theta_{R,\varepsilon_R}\right)}=\beta\left[f_R\varepsilon_R P_R-\omega_{R,\varepsilon_R}+\left(1-\delta\right)\frac{\kappa_{R,\varepsilon_R}}{q\left(\theta_{R,\varepsilon_R}\right)}\right]
$$

Substituting the wage function we have

$$
\frac{\kappa_{R,\varepsilon_R}}{q\left(\theta_{R,\varepsilon_R}\right)}=\beta\left[f_R\varepsilon_R P_R-\frac{1}{1+\frac{1-\tau}{\tau}\frac{1}{1-\sigma}}\left[f_R\varepsilon_R P_R+\theta_{R,\varepsilon_R}\kappa_{R,\varepsilon_R}\right]+\left(1-\delta\right)\frac{\kappa_{R,\varepsilon_R}}{q\left(\theta_{R,\varepsilon_R}\right)}\right]
$$

and once we add the assumption that hiring cost if proportional to productivity we get

$$\frac{\kappa_0}{q(\theta_{R,\varepsilon_R})} = \beta \left[1 - \frac{1}{1 + \frac{1-\tau}{\tau}\frac{1}{1-\sigma}}\left[1 + \theta_{R,\varepsilon_R}\kappa_0\right] + (1-\delta)\frac{\kappa_0}{q(\theta_{R,\varepsilon_R})}\right]$$

$$\frac{\kappa_0}{q(\theta_{R,\varepsilon_R})}(1 - \beta(1-\delta)) = \beta \frac{\frac{1-\tau}{\tau}\frac{1}{1-\sigma} - \theta_{R,\varepsilon_R}\kappa_0}{1 + \frac{1-\tau}{\tau}\frac{1}{1-\sigma}}$$

$$\kappa_0 \left[\frac{1 - \beta(1-\delta)}{q(\theta_{R,\varepsilon_R})} + \beta \frac{\theta_{R,\varepsilon_R}}{1 + \frac{1-\tau}{\tau}\frac{1}{1-\sigma}}\right] = \beta \frac{\frac{1-\tau}{\tau}\frac{1}{1-\sigma}}{1 + \frac{1-\tau}{\tau}\frac{1}{1-\sigma}}$$

$$\kappa_0 = \frac{\beta \frac{\frac{1-\tau}{\tau}\frac{1}{1-\sigma}}{1 + \frac{1-\tau}{\tau}\frac{1}{1-\sigma}}}{\frac{1-\beta(1-\delta)}{q(\theta_{R,\varepsilon_R})} + \beta \frac{\theta_{R,\varepsilon_R}}{1 + \frac{1-\tau}{\tau}\frac{1}{1-\sigma}}}$$

A.6. Productivity cutoffs

Denote the value of staying out of the labor force by $V_{o,\varepsilon}$, a constant number in steady state.

The value of employment in occupation R with idiosyncratic productivity ε_R is

$$V_{e,R,\varepsilon} = \frac{\left(\omega_{R,\varepsilon_R}\left(1-T_{e,R,\varepsilon_R}\right)\right)^{1-\sigma}}{1-\sigma} + \beta\left(1-\delta\right)V_{e,R,\varepsilon} + \beta\delta V_{u,R,\varepsilon}$$

$$V_{e,R,\varepsilon} = \frac{1}{1-\beta\left(1-\delta\right)}\left[\frac{\left(\frac{f_R\varepsilon_R P_R}{1+\frac{1-\tau}{\tau}\frac{1}{1-\sigma}}\left[1+\theta_{R,\varepsilon_R}\kappa_0\right]\left(1-T_{e,R,\varepsilon_R}\right)\right)^{1-\sigma}}{1-\sigma}\right] + \frac{\beta\delta}{1-\beta\left(1-\delta\right)}V_{u,R,\varepsilon}$$

where we substituted the explicit wage function under the assumption of proportional hiring costs.

The value of unemployment in occupation R with idiosyncratic productivity ε_R is

$$V_{u,R,\varepsilon} = \frac{\left(b_{R,\varepsilon_R}\omega_{R,\varepsilon_R}\left(1-T_{u,R,\varepsilon_R}\right)\right)^{1-\sigma}}{1-\sigma} + \beta\left(1-\mu\left(\theta_{R,\varepsilon_R}\right)\right)V_{u,R,\varepsilon} + \beta\mu\left(\theta_{R,\varepsilon_R}\right)V_{e,R,\varepsilon}$$

$$V_{u,R,\varepsilon}\left(1-\beta\right) = \left[\frac{\left(b_{R,\varepsilon_R}\frac{f_R\varepsilon_R P_R}{1+\frac{1-\tau}{\tau}\frac{1}{1-\sigma}}\left[1+\theta_{R,\varepsilon_R}\kappa_0\right]\left(1-T_{u,R,\varepsilon_R}\right)\right)^{1-\sigma}}{1-\sigma}\right] + \beta\mu\left(\theta_{R,\varepsilon_R}\right)\left[V_{e,R,\varepsilon}-V_{u,R,\varepsilon}\right]$$

Note that the first order condition of the bargaining problem implies that

$$V_{e,R,\varepsilon} - V_{u,R,\varepsilon} = \xi\frac{\tau}{1-\tau}\frac{1}{1-T_\pi}\frac{\partial J\left(x_{R,\varepsilon_R},\Lambda\right)}{\partial x_{R,\varepsilon_R}}$$

and the first order condition with respect to vacancies implies that

$$\frac{\partial J\left(x_{R,\varepsilon_R},\Lambda\right)}{\partial x_{R,\varepsilon_R}} = \frac{\left(1-T_\pi\right)\kappa_0 P_R f_R \varepsilon_R}{\beta q\left(\theta_{R,\varepsilon_R}\right)}$$

Substituting, we have

$$V_{u,R,\varepsilon}\left(1-\beta\right) = \left[\frac{\left(b_{R,\varepsilon_R}\frac{f_R\varepsilon_R P_R}{1+\frac{1-\tau}{\tau}\frac{1}{1-\sigma}}\left[1+\theta_{R,\varepsilon_R}\kappa_0\right]\left(1-T_{u,R,\varepsilon_R}\right)\right)^{1-\sigma}}{1-\sigma}\right]$$
$$+\theta_{R,\varepsilon_R}\xi\frac{\tau}{1-\tau}\kappa_0 P_R f_R \varepsilon_R$$

Now we can substitute for ξ, taking into account the CRRA assumption

$$\begin{aligned}
\xi &= U'\left(C_{e,R,\varepsilon}\right)\left(1-T_{e,R,\varepsilon}\right) - U'\left(C_{u,R,\varepsilon}\right)\left(1-T_{u,R,\varepsilon}\right) b_{R,\varepsilon} \\
&= \left(\omega_{R,\varepsilon_R}\right)^{-\sigma}\left[\left(1-T_{e,R,\varepsilon}\right)^{1-\sigma} - \left(1-T_{u,R,\varepsilon}\right)^{1-\sigma} b_{R,\varepsilon}^{1-\sigma}\right] \\
&= \left(\frac{f_R \varepsilon_R P_R}{1+\frac{1-\tau}{\tau}\frac{1}{1-\sigma}}\left[1+\theta_{R,\varepsilon_R}\kappa_0\right]\right)^{-\sigma}\left[\left(1-T_{e,R,\varepsilon}\right)^{1-\sigma} - \left(1-T_{u,R,\varepsilon}\right)^{1-\sigma} b_{R,\varepsilon}^{1-\sigma}\right]
\end{aligned}$$

Therefore

$$\begin{aligned}
V_{u,R,\varepsilon}\left(1-\beta\right) &= \left[\frac{\left(b_{R,\varepsilon_R}\frac{f_R\varepsilon_R P_R}{1+\frac{1-\tau}{\tau}\frac{1}{1-\sigma}}\left[1+\theta_{R,\varepsilon_R}\kappa_0\right]\left(1-T_{u,R,\varepsilon_R}\right)\right)^{1-\sigma}}{1-\sigma}\right] \\
&+ \left(\frac{f_R \varepsilon_R P_R}{1+\frac{1-\tau}{\tau}\frac{1}{1-\sigma}}\left[1+\theta_{R,\varepsilon_R}\kappa_0\right]\right)^{-\sigma}\left[\left(1-T_{e,R,\varepsilon}\right)^{1-\sigma} - \left(1-T_{u,R,\varepsilon}\right)^{1-\sigma} b_{R,\varepsilon}^{1-\sigma}\right]\theta_{R,\varepsilon_R}\frac{\tau}{1-\tau}\kappa_0 P_R f_R \varepsilon_R \\
&= \left(f_R P_R \varepsilon_R\right)^{1-\sigma}\left[\begin{array}{l}\frac{\left(b_{R,\varepsilon_R}\frac{1+\theta_{R,\varepsilon_R}\kappa_0}{1+\frac{1-\tau}{\tau}\frac{1}{1-\sigma}}\left(1-T_{u,R,\varepsilon_R}\right)\right)^{1-\sigma}}{1-\sigma} + \\ \left(\frac{1+\theta_{R,\varepsilon_R}\kappa_0}{1+\frac{1-\tau}{\tau}\frac{1}{1-\sigma}}\right)^{-\sigma}\left[\left(1-T_{e,R,\varepsilon}\right)^{1-\sigma} - \left(1-T_{u,R,\varepsilon}\right)^{1-\sigma} b_{R,\varepsilon}^{1-\sigma}\right]\theta_{R,\varepsilon_R}\frac{\tau}{1-\tau}\kappa_0\end{array}\right]
\end{aligned}$$

or

$$V_{u,R,\varepsilon} = \frac{\left(f_R P_R \varepsilon_R\right)^{1-\sigma}}{1-\beta}\left[\begin{array}{l}\frac{\left(b_{R,\varepsilon_R}\frac{1+\theta_{R,\varepsilon_R}\kappa_0}{1+\frac{1-\tau}{\tau}\frac{1}{1-\sigma}}\left(1-T_{u,R,\varepsilon_R}\right)\right)^{1-\sigma}}{1-\sigma} + \\ \left(\frac{1+\theta_{R,\varepsilon_R}\kappa_0}{1+\frac{1-\tau}{\tau}\frac{1}{1-\sigma}}\right)^{-\sigma}\left[\left(1-T_{e,R,\varepsilon}\right)^{1-\sigma} - \left(1-T_{u,R,\varepsilon}\right)^{1-\sigma} b_{R,\varepsilon}^{1-\sigma}\right]\theta_{R,\varepsilon_R}\frac{\tau}{1-\tau}\kappa_0\end{array}\right]$$

Note that the term in brackets is constant in steady state because it is a combination of exogenous parameters and the tightness ratio, which we have shown to be independent of the productivity parameters. Defining the term in brackets by $\urcorner_R$ and the analogue for NRM by $\urcorner_{NRM}$ we can express the values of unemployment in both occupations as

$$V_{u,R,\varepsilon} = \frac{(f_R P_R \varepsilon_R)^{1-\sigma}}{1-\beta} \daleth_R$$

$$V_{u,R,\varepsilon} = \frac{(f_{NRM} P_{NRM} \varepsilon_{NRM})^{1-\sigma}}{1-\beta} \daleth_{NRM}$$

A.7. Derivation of change in welfare by group

We explain here the derivation of welfare changes discussed in section 4.3. Consider first those who choose the routine occupational market both pre- and post-automation. 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:

$$V_{u,\varepsilon_R,\varepsilon_{NRM}} = \frac{(f_R P_R \varepsilon_R)^{1-\sigma}}{1-\beta} \neg_R.$$

The steady state value of being employed is given by:

$$V_{e,\varepsilon_R,\varepsilon_{NRM}} = \left[\frac{\frac{\left(1-\beta(1-\mu(\theta_{\varepsilon_R}))\right)}{1-\beta} \neg_R - \frac{b^{1-\sigma}}{1-\sigma}}{\beta\mu(\theta_{\varepsilon,R})} \right] (f_R P_R \varepsilon_R)^{1-\sigma}.$$

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:

$$V_{\varepsilon_R,\varepsilon_{NRM}} = UR_{\varepsilon_R} V_{u,\varepsilon_R,\varepsilon_{NRM}} + ER_{\varepsilon_R} V_{e,\varepsilon_R,\varepsilon_{NRM}}.$$

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

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

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

$$\Delta_{R^{OLD}\to R^{NEW}} = \frac{\left[UR_{\varepsilon_R} \frac{\neg_R}{1-\beta} + ER_{\varepsilon_R} \left[\frac{\frac{(1-\beta(1-\mu(\theta_{\varepsilon_R})))}{1-\beta} \neg_R - \frac{b^{1-\sigma}}{1-\sigma}}{\beta\mu(\theta_{\varepsilon_R})} \right] \right]^{\frac{1}{1-\sigma}} f_R P_R^{NEW} E(\varepsilon_R)^{R^{OLD}\to R^{NEW}}}{\left[UR_{\varepsilon_R} \frac{\neg_R}{1-\beta} + ER_{\varepsilon_R} \left[\frac{\frac{(1-\beta(1-\mu(\theta_{\varepsilon_R})))}{1-\beta} \neg_R - \frac{b^{1-\sigma}}{1-\sigma}}{\beta\mu(\theta_{\varepsilon_R})} \right] \right]^{\frac{1}{1-\sigma}} f_R P_R^{OLD} E(\varepsilon_R)^{R^{OLD}\to R^{NEW}}} = \frac{P_R^{NEW}}{P_R^{OLD}},$$

where $E(\varepsilon_R)^{R^{OLD}\to R^{NEW}}$ denotes the average ability of those who remain in R.

We apply a similar approach to calculate welfare ratios for the other transitions. The welfare change due to automation for those who switched form R to NRM is given by

$$\Delta_{R^{OLD}\rightarrow NRM^{NEW}}=\frac{\left[\begin{array}{l}\frac{UN_{\varepsilon_{NRM}}}{EMP_{\varepsilon_{NRM}}+UN_{\varepsilon_{NRM}}}\frac{\daleth_{NRM}}{1-\beta}+\\ \frac{EMP_{\varepsilon_{NRM}}}{EMP_{\varepsilon_{NRM}}+UN_{\varepsilon_{NRM}}}\left(\frac{\frac{\left(1-\beta\left(1-\mu\left(\theta_{\varepsilon_{NRM}}\right)\right)\right)}{1-\beta}\daleth_{R}-\frac{b_{\varepsilon_{NRM}}^{1-\sigma}\left(1-T_{u,\varepsilon_{NRM}}\right)^{1-\sigma}}{1-\sigma}}{\beta\mu\left(\theta_{\varepsilon,NRM}\right)}\right)\end{array}\right]^{\frac{1}{1-\sigma}} f_{NRM}P_{NRM}^{NEW}E\left(\varepsilon_{NRm}\right)^{R^{OLD}\rightarrow NRM^{NEW}}}{\left[\begin{array}{l}\frac{UN_{\varepsilon_{R}}}{EMP_{\varepsilon_{R}}+UN_{\varepsilon_{R}}}\frac{\daleth_{R}}{1-\beta}+\\ \frac{EMP_{\varepsilon_{R}}}{EMP_{\varepsilon_{R}}+UN_{\varepsilon_{R}}}\left(\frac{\frac{\left(1-\beta\left(1-\mu\left(\theta_{\varepsilon_{R}}\right)\right)\right)}{1-\beta}\daleth_{R}-\frac{b_{\varepsilon_{R}}^{1-\sigma}\left(1-T_{u,\varepsilon_{R}}\right)^{1-\sigma}}{1-\sigma}}{\beta\mu\left(\theta_{\varepsilon,R}\right)}\right)\end{array}\right]^{\frac{1}{1-\sigma}} f_{R}P_{R}^{OLD}E\left(\varepsilon_{R}\right)^{R^{OLD}\rightarrow NRM^{NEW}}}$$

which given our calibration targets can be simplified to

$$\Delta_{R^{OLD}\rightarrow NRM^{NEW}}=\frac{f_{NRM}P_{NRM}^{NEW}E\left(\varepsilon_{NRm}\right)^{R^{OLD}\rightarrow NRM^{NEW}}}{f_{R}P_{R}^{OLD}E\left(\varepsilon_{R}\right)^{R^{OLD}\rightarrow NRM^{NEW}}}$$

where we note that in the numerator we draw the ε_{NRM} abilities for these individuals that transitions to NRM.

The average change in welfare for R workers who leave the labor force is given by

$$\Delta_{R^{OLD}\rightarrow NLF^{NEW}}=\frac{\frac{1}{1-\beta}\frac{1}{1-\sigma}\left(b_{O}\right)^{\frac{1}{1-\sigma}}}{\left[\begin{array}{l}\frac{UN_{\varepsilon_{R}}}{EMP_{\varepsilon_{R}}+UN_{\varepsilon_{R}}}\frac{\daleth_{R}}{1-\beta}+\\ \frac{EMP_{\varepsilon_{R}}}{EMP_{\varepsilon_{R}}+UN_{\varepsilon_{R}}}\left(\frac{\frac{\left(1-\beta\left(1-\mu\left(\theta_{\varepsilon_{R}}\right)\right)\right)}{1-\beta}\daleth_{R}-\frac{b_{\varepsilon_{R}}^{1-\sigma}\left(1-T_{u,\varepsilon_{R}}\right)^{1-\sigma}}{1-\sigma}}{\beta\mu\left(\theta_{\varepsilon,R}\right)}\right)\end{array}\right]^{\frac{1}{1-\sigma}} f_{R}P_{R}^{OLD}E\left(\varepsilon_{R}\right)^{R^{OLD}\rightarrow NLF^{NEW}}}$$

Note that by definition, there is an individual who is indifferent between participating in the labor force and not. Then, since the value of being outside of the labor force does not change in this analysis, we can rewrite the above expression as

$$\Delta_{R^{OLD}\rightarrow NLF^{NEW}}=\frac{\varepsilon_{R}^{*,OLD}}{E\left(\varepsilon_{R}\right)^{R^{OLD}\rightarrow NLF^{NEW}}}$$

The average change in the consumption equivalence for those who worked in Non-Routine Manual occupations, and continued working in Non-Routine Manual occupations is given by

$$\Delta_{NRM^{OLD}\rightarrow NRM^{NEW}}=\frac{P_{NRM}^{NEW}}{P_{NRM}^{OLD}}$$

The average change in consumption equivalent welfare for those who were outside the labor force and started working in Non-Routine-Manual occupations post-automation is given by

$$\Delta_{NLF^{OLD}\rightarrow NRM^{NEW}}=\left[\begin{array}{l}\dfrac{UN_{\varepsilon_{NRM}}}{EMP_{\varepsilon_{NRM}}+UN_{\varepsilon_{NRM}}}\dfrac{\neg_{NRM}}{1-\beta}+\\ \dfrac{EMP_{\varepsilon_{NRM}}}{EMP_{\varepsilon_{NRM}}+UN_{\varepsilon_{NRM}}}\left(\dfrac{\frac{\left(1-\beta(1-\mu(\theta_{\varepsilon_{NRM}}))\right)}{1-\beta}\neg_{NRM}-\frac{b_{\varepsilon_{NRM}}^{1-\sigma}\left(1-T_{u,\varepsilon_{NRM}}\right)^{1-\sigma}}{1-\sigma}}{\beta\mu(\theta_{\varepsilon,NRM})}\right)\end{array}\right]^{\frac{1}{1-\sigma}} \frac{f_{NRM}P_{NRM}^{NEW}E\left(\varepsilon_{NRM}\right)^{NLF^{OLD}\rightarrow NRM^{NEW}}}{\frac{1}{1-\beta}\frac{1}{1-\sigma}\left(b_O\right)^{\frac{1}{1-\sigma}}}$$

As above, given the cutoff value of those individuals who are outside the labor force we can rewrite this expression as

$$\Delta_{NLF^{OLD}\rightarrow NRM^{NEW}}=\frac{P_{NRM}^{NEW}E\left(\varepsilon_{NRM}\right)^{NLF^{OLD}\rightarrow NRM^{NEW}}}{P_{NRM}^{OLD}\varepsilon_{NRM}^{*,OLD}}$$

A.8. Alternative calibration of ρ

Table A8: Alternative calibration with $\rho = 0.5$

	Automation Capital Change	Retraining	UI	UBI	NLF Benefits	Taxation
Labor states						
Φ NLF	2.091	-2.149	-2.133	5.751	14.743	-5.013
Φ R	-3.896	0.526	1.584	-4.673	-11.279	3.709
Φ NRM	1.805	1.623	0.550	-1.078	-3.464	1.304
Emp. Rate R	0.950	0.95	0.945	0.945	0.950	0.950
Emp. Rate NRM	0.950	0.95	0.944	0.944	0.950	0.950
ΔY_{NRC}	1.200	0.379	0.119	-14.439	-7.858	-2.163
ΔY_R	-4.155	1.316	0.302	-4.648	-11.965	2.973
ΔY_{NRM}	9.664	4.144	-0.438	-3.548	-12.495	3.784
Δ GDP	12.140	1.327	0.282	-9.920	-9.748	0.195
Φ NRC labor tax	0.00	-1.524	-0.449	35.500	24.587	10.355
Wages						
$\Delta\omega_R$	-6.154	-0.093	0.516	-7.142	3.240	-4.112
$\Delta\omega_{NRM}$	2.149	-3.129	0.730	-6.139	2.747	-3.590
$\Delta\omega_{NRC}$	23.373	0.901	0.001	8.108	-3.587	4.451
$\Delta\omega_{NRC}$: after tax	23.373	0.766	0.157	-11.240	-9.151	-2.606
Welfare: Consumption Equivalence						
$\Delta : R^{Old} \to \Delta R^{New}$	-6.60	0.80	1.96	6.18	3.29	10.20
$\Delta : R^{Old} \to \Delta NRM^{New}$	-1.70	NA	2.34	9.09	NA	10.50
$\Delta : R^{Old} \to \Delta NLF^{New}$	-3.60	0.20	NA	26.50	16.50	NA
$\Delta : NRM^{Old} \to \Delta R^{New}$	NA	-1.00	NA	NA	3.04	NA
$\Delta : NRM^{Old} \to \Delta NRM^{New}$	2.50	-2.50	2.15	6.77	2.78	10.80
$\Delta : NRM^{Old} \to \Delta NLF^{New}$	NA	-1.60	NA	27.08	16.27	NA
$\Delta : NLF^{Old} \to \Delta R^{New}$	NA	NA	2.28	NA	NA	5.83
$\Delta : NLF^{Old} \to \Delta NRM^{New}$	1.90	10.44	2.39	NA	NA	6.10
$\Delta : NLF^{Old} \to \Delta NLF^{New}$	0.00	0.00	0.00	34.60	34.66	0.00
$\Delta : NRC^{Old} \to \Delta NRC^{New}$	22.30	2.05	0.72	-21.70	-22.50	-5.30

Notes: (i) Φ denotes percentage point change; (ii) Δ denotes percentage change; (iii) the reference point for the first column is the steady state *beofre* the Automation capital price decline; (iv) the reference point for columns 2-6 is the steady state *after* the Automation capital price decline.

Table A9: Alternative calibration with $\rho = -0.5$

	Automation Capital Change	Retraining	UI	UBI	NLF Benefits	Taxation
Labor states						
Φ NLF	2.258	-2.186	-2.356	6.202	15.624	-5.626
Φ R	-3.742	0.373	1.628	-4.897	-11.877	4.089
Φ NRM	1.484	1.733	0.723	-1.308	-3.837	1.533
Emp. Rate R	0.950	0.95	0.946	0.946	0.950	0.950
Emp. Rate NRM	0.950	0.95	0.946	0.946	0.950	0.950
ΔY_{NRC}	1.232	0.237	0.179	-13.886	-8.249	-1.882
ΔY_{R}	-3.335	0.053	-0.291	-5.671	-13.349	2.942
ΔY_{NRM}	5.458	6.160	-0.666	-4.868	-14.480	4.457
Δ GDP	11.894	0.733	-0.256	-10.422	-10.900	-0.095
Φ NRC labor tax	0.00	-1.281	-0.650	35.290	25.816	9.664
Wages						
$\Delta\omega_{R}$	-7.231	0.091	-0.303	-7.447	2.917	-4.788
$\Delta\omega_{NRM}$	6.434	-5.453	0.443	-5.604	3.529	-4.406
$\Delta\omega_{NRC}$	23.224	0.696	-0.435	6.972	-4.443	4.241
$\Delta\omega_{NRC}$: after tax	23.224	0.796	0.145	-14.375	-12.314	-3.051
Welfare: Consumption Equivalence						
$\Delta : R^{Old} \rightarrow \Delta R^{New}$	-7.00	1.42	1.78	6.24	3.65	10.00
$\Delta : R^{Old} \rightarrow \Delta NRM^{New}$	-0.40	NA	3.00	15.04	3.87	10.21
$\Delta : R^{Old} \rightarrow \Delta NLF^{New}$	-4.30	NA	NA	25.70	16.30	NA
$\Delta : NRM^{Old} \rightarrow \Delta R^{New}$	NA	-1.62	NA	NA	NA	NA
$\Delta : NRM^{Old} \rightarrow \Delta NRM^{New}$	6.64	-4.35	2.50	7.99	4.10	10.43
$\Delta : NRM^{Old} \rightarrow \Delta NLF^{New}$	NA	-2.55	NA	26.82	16.90	NA
$\Delta : NLF^{Old} \rightarrow \Delta R^{New}$	NA	0.90	2.16	NA	NA	5.71
$\Delta : NLF^{Old} \rightarrow \Delta NRM^{New}$	4.00	9.96	2.51	NA	NA	5.98
$\Delta : NLF^{Old} \rightarrow \Delta NLF^{New}$	0.00	0.00	0.00	33.60	33.60	0.00
$\Delta : NRC^{Old} \rightarrow \Delta NRC^{New}$	22.46	1.81	0.00	-22.50	-24.00	-5.30

Notes: (i) Φ denotes percentage point change; (ii) Δ denotes percentage change; (iii) the reference point for the first column are relative to the steady state *before* the Automation capital price decline; (iv) the reference point for columns 2-6 is the steady state *after* the Automation capital price decline.

A.9. Elasticity of unemployment duration to unemployment benefits

In the context of the UI and UBI experiment, a key channel through which these policies operate is via the bargaining problem and its impact on the wage and vacancies posting by firms. To discipline our analysis we required the model to match the elasticity of unemployment duration to unemployment benefits; different values of this elasticity have vastly different implications for the impact of different policy reforms. As such we require our model to match an elasticity value of 1, which is within the range of the empirical counterpart (see for example Meyer (1990) and Chetty (2008)).

To match this elasticity in the model we solve for the labor market equilibrium for different individuals and for different values of unemployment transfers. We then estimate the aggregate resulting tightness ratio and job finding rates, from which we calculate the elasticity of unemployment duration to unemployment transfers. We follow the approach in Yedid-Levi (2016) that allows us to match the elasticity of unemployment duration to unemployment benefits, while maintaining log preferences. In this modification we introduce an additional parameter that links the bargaining power of the worker with labor market tightness, in a way that tames the response of wages to changes in UI benefits. Formally, the bargaining power τ is now expressed as $\tau(\theta) = \frac{\tau_0}{\tau_0 + (1-\tau_0)\left(\frac{\theta^{ss}}{\theta}\right)^{\zeta}}$.[36]

Importantly, this implies that this alternative parametrization of the model does not affect any of the results presented until Section 6 since the value of τ is not changed as long as the tightness ratio does not deviate from its steady state value. Indeed in Section 5 following the Automation capital price change the tightness ratio is not altered.

To identify ζ we repeat the discussed above analysis and reestimate the elasticity of unemployment duration to unemployment benefits until the model matches the micro elasticity, converging on a value of $\zeta = 20$.

Thus to summarize, until section 6, given that the unemployment rate is constant, the elasticity of unemployment duration to unemployment benefits is quantitatively an irrelevant moment. In Section 6 where unemployment reacts to the changes in UI and UBI, we verify that the model matches the observed micro elasticity of unemployment duration to unemployment benefits.

[36] Note that when $\zeta = 0$ then the model converges to the benchmark case with constant bargaining power.