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

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

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Abstract

During the last four decades, the U.S. has experienced advances in automation and a fall in the employment in middle-wage, "routine-task-intensive," occupations. These processes have been at the center of policy discussions aimed at those who were adversely affected by automation. We contribute to these discussions by developing an empirically relevant general equilibrium model, featuring heterogeneous agents, labor force participation, occupational choice, and investment in physical and automation capital. We use this framework to evaluate the allocation and welfare distributional consequences of different polices. First, we consider the retraining of workers who were adversely affected by automation. Second, we consider redistribution policies that transfer resources to these workers. Our framework emphasizes general equilibrium effects such as displacement effects of retraining programs, complementarities between the various factors of production, and the effects of distortionary taxation that is required to fund these programs.

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

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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 employment decline 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).

The polarization of the labor market has fueled discussions about policy options targeted at helping those who were adversely affected by automation advances. In this paper, we contribute to this literature by focusing on the impact of different policy reforms within an empirically relevant, heterogeneous-agent general equilibrium macroeconomic model. Specifically, our model incorporates a labor force margin, alongside occupational choices; these are included because our empirical analysis suggests that (i) the transition to lower-paying occupations, and (ii) the transition out of the labor force are the two key margins of adjustment for those who are negatively affected by automation. The general equilibrium nature of the model, with its emphasis on heterogeneity, enables us to conduct and evaluate in a meaningful way the welfare implications of the retraining and redistribution policies we consider.

In what follows we discuss these contributions in detail. In Section 2, we document aggregate patterns that highlight the key labor margins of adjustment for those who used to work in routine occupations. Analyzing Current Population Survey (CPS) data we find that low-skill workers, who used to work in routine occupations, suffer a significant decline in their likelihood of working in routine occupations between the pre-polarization era and the post-polarization one. We find that the decline in employment in routine occupations for this group, can be accounted for by non-participation in the labor force (about two-thirds of it), and increased employment in low-paying non-routine manual occupations (about one third). These transitions are likely to have welfare consequences because leaving the labor force is likely to be accompanied by greater dependence on transfer payments, while a transition to non-routine manual occupations tends to be linked to a fall in wages and earnings (see, for instance, Autor and Dorn (2013)). We complement this analysis using the National Longitudinal Survey of the Youth (NLSY) 1979 and 1997, which gives us a direct measure of innate ability in the form of AFQT scores. With this measure we demonstrate that similar patterns are observed for young workers with low cognitive ability, who used to work in routine occupations in the late 1980s.

In Section 3 we turn to our general equilibrium model. Motivated by the findings of Section 2, we consider a model where unskilled individuals make a labor force decision and an occupation decision. In the model, unskilled individuals with routine occupational characteristics vary in terms of their work ability in routine (R) and non-routine manual (NRM) occupations that represent middle and low-paying jobs respectively.[1] Based on their abilities, the tax rate, the government transfers to those outside the labor force, and equilibrium wages, workers optimally decide whether to participate in the labor force and, conditional on doing so, sort into the two different unskilled occupations and decide their optimal hours of work. The model also features skilled workers employed in high-paying non-routine cognitive (NRC) occupations. On the production side, 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 employment in R and NRM occupations and the return to labor force participation. Our modeling approach is related to the recent contributions by Eden and Gaggl (2018) and vom Lehn (2019) who consider representative agent frameworks in their study of automation. Given our interest in welfare and policy analysis, as we discuss below, we study a richer framework featuring heterogeneous agents with an empirically realistic distribution of income and, key given our empirical findings, an endogenous labor force participation margin.

In Section 4 we calibrate the model and show that the acceleration of automation, modeled as a fall in the price of automation capital, induces, unsurprisingly, significant heterogeneity in welfare impact. The type of workers who used to be employed in routine occupations suffer a welfare loss, while high-skill NRC workers gain due to their complementarity with automation technology and because capital share goes up and they are the owners of firms in the economy.[2]

Given that automation creates welfare heterogeneity with clear "winners" and "losers," in Section 5 we move to the main part of the paper and use our model as a quantitative laboratory to evaluate the consequences for allocations and welfare of two types of redistributional policies. We begin by studying the effects of two different retraining programs. First, we consider one targeted at those who ended up outside the labor force and are thus at the bottom of the ability distribution, increasing their NRM ability. We calibrate this program based on similar existing programs such as the federal Trade Adjustment Assistance program (TAA). We then look at a program targeted at the group of routine workers with relatively high

[1] See for instance, Autor, Katz and Kearney (2006), Goos and Manning (2007), and Jaimovich and Siu (2020)).

[2] In a recent paper, Moll, Rachel and Restrepo (2021) discuss the role of automation in increasing the returns to wealth, and thus contributing to the raise in inequality.

ability, which trains them to perform NRC occupations. This experiment quantifies the effect of a program that provides high-skill routine workers with the equivalent of a four-year college education.

The retraining experiments we consider feature several forces at play that lead to an increased in GDP and labor force participation. In addition to the direct impact on the productivity of the retrained group, there are important general equilibrium effects present in our model. First, complementarities between the various factors of production trigger changes in the demand for all factors of production. Second, the retraining programs increase the supply of a specific type of labor (different across the programs), creating "displacement effects" where the trained individuals compete with incumbent workers in their occupation. Third, the programs affect the tax rate faced by high-wage NRC workers; on the one hand, given our interest in redistribution policies, we assume that the programs are funded by changes in the distortionary labor taxation borne by these NRC workers. On the other, the rise in labor force participation results in lower government transfers and hence a reduced tax burden. Overall, we find the latter effect to dominate and result in a reduction in the distortionary taxation levied on the NRC workers.

Our experiments reveal that, while both retraining programs raise GDP and labor force participation, their impact on welfare differs, due both to the direct retraining effect and to the equilibrium effects of the programs. In the unskilled retraining program, those non-participating low-skill workers enrolled in it gain directly. Moreover, the NRC, too, benefit from it thanks to complementarities in production. By contrast, due to the displacement effect, the welfare of incumbent low-wage workers in the NRM occupations declines. Similarly, in the NRC retraining program, those directly treated (the relatively high-ability routine workers in the program) gain. So do the untrained low-skilled thanks to their complementaries with NRC workers (the supply of whom increases) and to the reduced supply of low-skill workers retrained as NRC.

In both programs those directly retrained benefit – the non-participating low-skilled in the unskilled retraining program and the relatively high-ability routine workers in the NRC retraining program. In the former, due to the displacement effect, the welfare of the incumbent low-wage workers in the NRM occupations decreases, while the NRC gain due to complementarities in production. This contrasts with the latter program, in which the entry of new NRC workers leads to a fall in the NRC wage, so incumbent NRC workers suffer a drop-off in their welfare.

The second set of policy reforms that we analyze are direct redistribution programs. Specifically, we consider: (i) introducing a universal basic income program; (ii) increasing transfers to labor force non-participants; and (iii) making the tax system more progressive. All low-skilled workers (weakly) enjoy an increase in their welfare from these programs, while the NRC workers bear the costs and lose welfare-wise. The key difference across the programs is that the universal basic income (UBI) and the transfers to those outside the labor force trigger a fall in GDP and labor force participation, while making the tax system more progressive raises labor force participation, has no impact on GDP, and imposes relatively smaller welfare losses on the high-skilled.

Finally, highlighting the general equilibrium nature of the model and the endogenous accumulation of automation capital, we quantify the impact of the different policy programs on this type of capital. We show that some of the programs accelerate automation while others slow it down.

Section 6 concludes the paper, while the different Appendices discuss various empirical and theoretical robustness checks.

2. Employment and occupation trends

This section establishes the role of the different labor market adjustment margins for those who used to work in routine occupations during the 1980s (pre-polarization). It guides us in our modeling choices, such as incorporating a labor force margin alongside occupational choices.

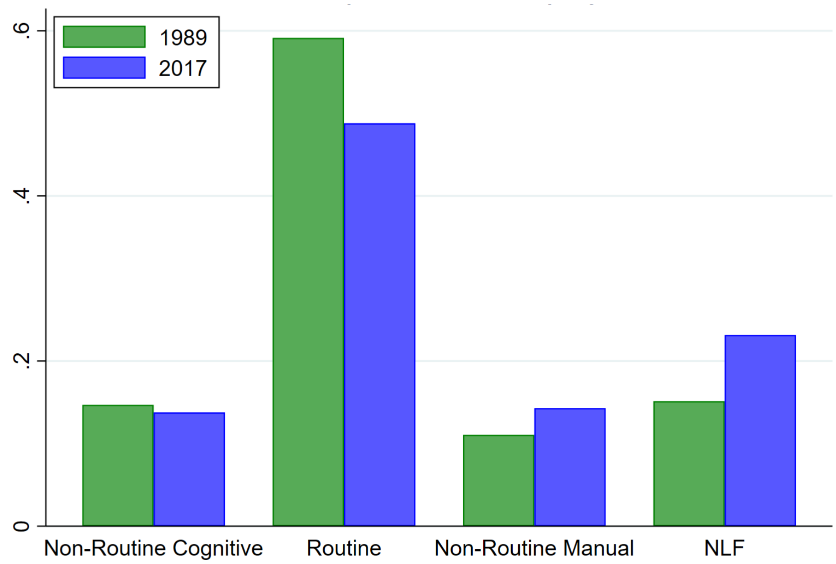
We first briefly survey the literature that establishes the relation between occupational trend and automation technologies. Next, we use data from the CPS and from the NLSY to identify the demographic groups that tended to work in routine occupations in the 1980s and to analyze the changes in their employment status and occupational choices over the last few decades.

An important literature documents the changes in the task content of work, its relation to the cost decline 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)).[3] While this literature comes to near-consensus about the drop in routine employment and its link to automation, less discussion has ensued about where workers likely to hold jobs with "routine occupational characteristics" during the pre-polarization period have ended 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? It is essential to answer these questions to construct an empirically relevant model that can be used for policy analysis.

CPS Data With these questions in mind, we start by classifying individuals according to their educational attainment. We split the population to low and high skill, and define high-skill workers as those with at

[3] See an emerging literature that evaluates the causal relation between automation and robotics on employment in general (e.g. Michaels, Natraj and Van Reenen (2014), Graetz and Michaels (2018) , Acemoglu and Restrepo (2019)), and specifically on routine vs. non-routine employment (e.g. Gaggl and Wright (2017) and Tuzel and Zhang (2019)).

Figure 1: Changes in Employment and Occupational Composition for Low-Skilled Men



Notes: Authors' calculations using CPS data for 1989 and 2017. Sample includes all men aged 18 to 65. Low-skilled defined as no college degree. Unemployed counted in their last occupation and unemployment rate is constant within low-skilled between the periods. Share of low-skilled declines from 76% to 70% over the same period

least a college degree.[4][5] We use the monthly CPS data from 1989 to 2017 to follow employment status and occupational composition for individuals in the low-skill group, which we also refer to as the *non-NRC* (compared to the high-skill *NRC* group). 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)).[6] The idea behind the low/high split is that low-skill workers are likelier to work in R and NRM occupations, so focusing on the changes in stocks of these individuals sheds light on where these workers, who tended to work in non-NRC occupations in the late 1980s, ended up in the 2017.

Figure 1 shows the fraction of low-skill (no college degree) men aged 18 to 65 who are labor force non-

[4]Cortes, Jaimovich and Siu (2017) 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 male high school graduates. They show that, in an accounting sense, men in this demographic group end up in low-paying non-routine manual jobs, or not working at all. See also Cortes (2016) who documents that large differences in characteristics exist between high- and low-skill worker types.

[5]In a previous version Jaimovich et al. (2020) we used an agnostic machine-learning approach to define the characteristics that classify workers into different occupation categories. In this exercise we used gender, education, age, and race (as well as other characteristics in some specifications). The most informative characteristic according to the machine-learning classification algorithm was education, and the results obtained using this approach resemble to the ones presented below.

[6]This occupational classification draws distinctions based on task intensity according to two factors. The first is whether an occupation is routine or non-routine. The second relates to whether the task is "cognitive" versus "manual." 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 (2020) (see details in Appendix A.1).

participation (NLF), employed in NRC, employed in R, or employed in NRM. The figure compares data from 1989 and 2017. Two important points emerge from this analysis. First, consistent with the findings in existing literature, we observe a large (17%) decline in employment in routine occupations within the low-skill group. Second, this drop, naturally, has to be offset by an increase in the other three statuses: non-participation or employment either in (high-wage) NRC or in (low-wage) NRM occupations. Indeed, the probability of NLF increased dramatically from 0.151 to 0.231, and the probability of employment in NRM occupations rose from about 0.111 to 0.143. At the same time, within low skill men the share in NRC occupations decreased from 0.147 in 1989 to 0.138 by 2017. To summarize, the decline in routine employment within the low-skill group was coupled with a fall in labor force participation and a rise in employment in low-wage NRM occupations.[7]

The patterns of women mirror those of men, though over a different time period. As is well known, female labor force participation exhibited a pronounced increase from 1960 to 2000. But since the turn of the twenty-first century it has plateaued and even began to fall among the prime-aged. As such, the period since the turn of the century is more indicative of female occupational dynamics. Figure A1 presents the same information as Figure 1, but for low-skill women, 2001-2017. In line with the menâs patterns discussed above, roughly two-thirds of the decline in routine employment can be traced to the increase in NLF, and the rest to higher NRM employment. This is a key takeaway of our analysis: the decline in routine employment for the low-skilled is accounted for by non-participation in the labor force and employment in NRM occupations.

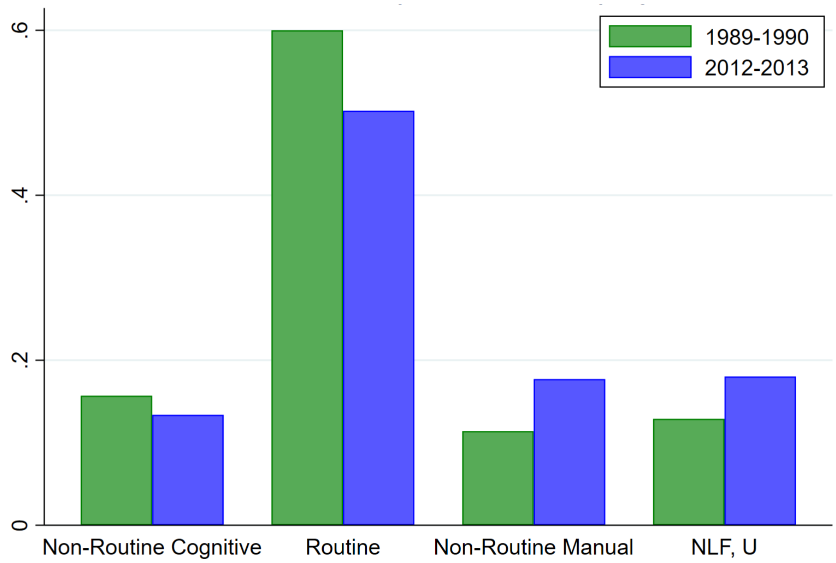
NLSY Data A shortcoming of the approach we used when analyzing the CPS data is that it relies on workers' observed educational attainment—a variable potentially endogenous to the automation forces under consideration. We address this concern by using respondents' AFQT score as measured in the NLSY; the AFQT measure is arguably a more direct and exogenous proxy for cognitive ability.[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 work in R in these deciles). Figure 2 compares the labor market status and occupational composition for workers in these deciles in 1989-1990 (using the NLSY79) and 2012-2013 (using the NLSY97).[9] The changes in participation and occupational choice for these men (of approximately 29.5 years of age) are

[7] These patters are consistent with the recent findings in Heathcote, Perri and Violante (Forthcoming) who emphasize that skill-biased technical change worsens the labor market opportunities of low-skill men pushing them outside of the labor force.

[8] See Appendix A.3 for a detailed discussion about the NLSY analysis

[9] We note that, because we recover occupations from employment reports in the NLSY 1997, we lump unemployed in with those with NLF status.

Figure 2: Changes in Employment and Occupational Composition for Low Cognitive Ability Men



Notes: Authors' calculations using NLSY data. Low cognitive ability is defined as deciles 2-4 of AFQT score. 1989-1990 uses NLSY 1979, while 2012-2013 uses NLSY 1997. Average age is 29.5 in both samples.

consistent with the patterns discussed above when using the CPS (for all prime working ages). There is a large falloff in the likelihood of routine employment (of 16% as in the CPS analysis above), accompanied by greater likelihood of non-participation and non-routine manual employment. The split between these two channels is roughly half-half. That there is more movement into non-routine manual 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.

3. Model

Motivated by the findings of Section 2, our model has two types of agents. We refer to them as high-skill (NRC) and low-skill (non-NRC) agents for simplicity. The low-skill agents are heterogeneous as each individual is endowed with a pair of idiosyncratic productivity parameters – one for occupation R and one for occupation NRM. Given their abilities in each occupation, these workers choose whether to participate in the labor force and, conditional on participation, in which frictionless occupational market to work and for how many hours.

The high-skilled, supply their labor in a frictionless labor market. For tractability, we assume that they are identical and work only in an NRC occupation and that they are the "capitalists" who own all firm equity in the economy. Low-skill workers are excluded from asset/credit markets and are "hand-to-mouth," with current consumption equal to current income.[10]

In terms of capital we assume two capital inputs in the form of automation capital and non-automation capital, which are used in final production. Both capital stocks are owned by perfectly competitive, final good producers who make investment decisions. Therefore, in the model, the degree of automation capital accumulation is endogenous.

Finally, to allow for the analysis of various government policies, we incorporate the following taxes and transfers: a proportional tax on firms' profits, a progressive tax on labor income, and transfers to labor force non-participants.

Our modeling approach is related to the recent contributions of 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. 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 optimally select themselves 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 of low-skill workers. Second, allowing for heterogeneity in the economy as well as labor force participation is critical for the welfare analysis if one is to consider the implications of policy changes.

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: three labor occupational inputs 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:

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

[10]Given our interest in heterogeneity within the low-skill workers, allowing asset accumulation for this group implies that we will need to track the distribution of wealth across these individuals a-la Aiyagari (1994) which goes beyond the scope of the paper. Moreover, while this assumption might amplify the welfare implications of our policy analysis discussed below, it has in fact empirical traction. For example, the Survey of Consumer Finances (SCF) reports median household net worth by the educational level of household heads. Over the 1989-2016 period, median net worth of college graduates exceeded high school dropouts' by more than 12 times and high school graduates' by more than 4 times. Thus, highly educated individuals, who are empirically NRC worker types (as documented in Section 2), own the vast majority of assets in the U.S.

Final good producers accumulate physical and automation capital (which depreciate at rates δ_K and δ_A, respectively) and purchase the three intermediate goods at prevailing prices.[11] The relative price of investment in non-automation capital is denoted ϕ_K and the relative price of automation 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

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

where T_π is a tax rate on firms' profits, Q is the stochastic discount factor which we define below, 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,[12] which are either exogenously specified or determined in equilibrium.[13]

3.1.1. Labor occupational inputs

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

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

where Pop_{NRC} denotes the population share of high-skilled workers, f_R denotes occupation specific productivity level, h_{ε_R} denotes the hours worked of an individual with ε_R efficiency units, $\Gamma'(\varepsilon_R, \varepsilon_{NRM})$ denotes the density function associated with the distribution function, Γ, and h_{ε_R} denotes hours worked (per labor force participant) for a given ability level, ε_R.

As we discuss in Appendix A.4, 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. This allows us to have the term ε_R^* in Equation (2) denoting the cutoff

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

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

ability in R such that all those with lesser ability do not work in R. Similarly, 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, and we do not repeat its exposition for brevity. Finally, since our primary interest is in the low-skill labor market, we assume for simplicity that high-skill workers always participate in the labor market, make no occupational choice and work only in NRC production, and are identical in ability (normalized to unity) and therefore in their optimal choice of hours worked. Thus $Y_{NRC} = f_{NRC}Pop_{NRC}h_{NRC}$, where f_{NRC} is the occupation-specific productivity level and h_{NRC} denotes the hours worked by a NRC worker.

3.2. Workers

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

3.2.1. Non-Routine Cognitive workers

High-skill (NRC) workers, have preferences over consumption, C_{NRC} denoted by the utility $U(C_{NRC})$, and derive disutility from hours spent working, h_{NRC} denoted by $G(h_{NRC})$.[14] They earn ω_{NRC} per hour worked and are taxed on labor income at the rate T_{NRC}.[15] High-skill workers save in the form of an asset that represents claims to firms' profits. 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

$$
\begin{aligned}
&V_{NRC}(B_{NRC},\Lambda) = \max_{C_{NRC},h_{NRC},B'_{NRC}} \left\{U(C_{NRC}) - G(h_{NRC}) + \beta\left[V_{NRC}\left(B'_{NRC},\Lambda'\right)\right]\right\} \qquad (3)\\
&\text{s.t.:}\quad C_{NRC} + pB'_{NRC} = h_{NRC}\omega_{NRC}(1-T_{NRC}) + pB_{NRC} + (1-T_\pi)\pi
\end{aligned}
$$

This problem defines the stochastic discount factor, Q, with which the firm discounts its continuation value, i.e. $Q = \beta\frac{U'(C_{NRC})}{U'\left(C'_{NRC}\right)}$.

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

[15] 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.

3.2.2. Routine and Non-Routine Manual workers

Similar to NRC workers, the unskilled have separable preferences over consumption and hours spent working. Unlike NRC workers, non-NRC individuals make a labor force participation and an occupation decision.

Formally, let $(\varepsilon_R, \varepsilon_{NRM})$ denote a worker's (constant) idiosyncratic ability draw pair. Given these draws a low-skill worker simultaneously chooses whether to participate in the labor market or not and, conditional on participating, in which occupational labor market to work and for how many hours. Given our assumptions that (i) only NRC workers hold assets in the economy and (ii) that labor markets are frictionless, the decision problem of these workers is static and simply amounts to a comparison of contemporaneous utility that takes into account the current period consumption and the optimal hours worked when employed in a given occupation.

Hence, if working in the R occupation then the consumption C_{e,ε_R}, must satisfy the budget constraint:

$$C_{e,\varepsilon_R} = \omega_R h_{\varepsilon_R} \varepsilon_R \left(1 - T_R\right),$$

where ω_R denotes the wage per efficiency unit, h_{ε_R} denotes the optimal hours worked, and T_R is the income tax rate. The problem for workers employed in an NRM occupation is identical in structure to that just described, except with R-subscripts replaced by NRM-subscripts.

Finally, a worker who decides to be out of the labor force receives a transfer that is constant and independent of ability,

$$C_o = b_o.$$

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 different likelihoods of labor force participation following a change in the economy.

3.3. Government budget constraint

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

$$NLF \times b_o = Rev_{NRC} + Rev_R + Rev_{NRM} + Rev_\pi, \tag{4}$$

where NLF denote the measure of low-skill workers outside the labor force:

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

and thus total government transfers to this group equal $NLF \times b_o$.

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

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

and :

$$Rev_R = (1 - Pop_{NRC}) \int_{\varepsilon_R^*}^{\infty} \int_{-\infty}^{\varepsilon_{NRM}(\varepsilon_R)} h_{\varepsilon_R} T_R \omega_R \Gamma'(\varepsilon_R, \varepsilon_{NRM}) d\varepsilon_{NRM} d\varepsilon_R,$$

respectively. Labor taxes collected from NRC workers is:

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

Tax revenues from the final good producer are given by:

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

3.4. Equilibrium

To summarize the structure of the model, a fraction of workers is high-skill. They supply their labor in a frictionless labor market to 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 $\Gamma(\varepsilon_R, \varepsilon_{NRM})$. These workers choose whether and in which occupational market to participate, and choose how many hours to supply in that market.

Hence, formally, given productivities $\{f_R, f_{NRM}, f_{NRC}\}$, the relative prices of capital $\{\phi_K, \phi_A\}$, 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 is a collection of:

- wages per NRC worker $\{\omega_{NRC}\}$ and per efficiency units in R and NRM $\{\omega_R, \omega_{NRM}\}$;
- prices of the occupational outputs P_{NRC}, P_{NRM}, P_R;
- price of equity claims p;

- labor input and capital, $\{Y, Y_{NRC}, Y_R, Y_{NRM}, K, X_A\}$; and
- policy, $\{T_\pi, T_{NRC}, b_o\}$ and $\{T_R, T_{NRM}\}$

such that

- final good firms are profit maximizing,
- workers are utility maximizing (specifically, high-skill workers are making saving and labor supply decisions, and low-skill workers are making decisions about participation, occupation, and hours of work optimally),
- the final good market clears,
- labor market of the three factors of production clears,
- the equity market clears: $B_{NRC} = 1$, and
- the government's budget constraint is satisfied.

4. Calibration

In this section we calibrate the model economy, which targets, in general, data moments for 2017. 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.

Ability distribution We assume the work ability distribution, $\Gamma(\varepsilon_R, \varepsilon_{NRM})$, to be jointly log normal. As we discuss in Appendix A.5, to identify the parameters of this distribution we use the observed shares of low-skill workers in the routine and non-routine manual occupations in 2017 and the variance of observed R and NRM wages in the data. We note that the correlation between the two abilities cannot be identified in the data. As such, we solve the model for various values of this correlation. Quantitatively, as shown in the tables in Appendix A.7, all of the results that we present below and in the policy experiments are very similar for different values of this correlation.

Table 1: Calibration

Parameter	Value	Target
Ability Distribution		
μ_{NRM}	1	Normalization
μ_R	1	
σ_{NRM}	1.0069	Occupations allocations and variance of observed wages
σ_R	0.7509	
$\rho_{R,NRM}$	0	See text for details
Preferences		
β	0.9615	Annual frequency; $r_{annual} = 0.04$
$\eta_R, \eta_{NRM}, \eta_{NRC}$	1	see text
Taxes and Transfers		
b_o	0.0284	Indifference condition for participation
T_{NRM}	0.137	Average group tax rates
T_R	0.137	
T_{NRC}	0.267	
T_{Π}	0.36	See Trabandt and Uhlig (2011)
Depreciation Rates		
δ_K	0.12	see Eden and Gaggl (2018)
δ_A	0.19	
Production Function: Shares and Elasticities		
ψ	.1099	Labor share, Routine Labor Share, ICT capital Income share
α	0.8154	
f_R	0.1575	
γ	0.31	Physical capital income share (see Eden and Gaggl (2018))
ν	0.47	Split of R workers between NLF and NRM and $\Delta\frac{X_A}{\phi_A}$
ς	-2.1	

Preferences The model is calibrated to an annual frequency. We set $\beta = 0.9615$, targeting an average annual risk-free interest rate of 4%. We assume a separable flow utility $u(C,h) = \log(C) - \chi_j \frac{h^{1+\eta_j}}{1+\eta_j}$, where $j = \{R, NRM, NRC\}$. We set $\eta_j = 1$ and solve for χ_j such that h is normalized to 1 in steady state for all workers.[16]

Government transfers The value of the government transfer to those who do not participate in the labor force is set internally to ensure that, when calibrated to match the 2017 shares of workers in R, NRM, and NLF, the marginal $(\varepsilon_R^*, \varepsilon_{NRM}^*)$ worker is indifferent as to participating in the labor force or being unemployed.[17]

Taxes Government transfers are funded by taxes on profits and labor income. The labor tax schedule is progressive. We set the tax on non-participants' 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 the high-skill/NRC tax rate is set at $T_{NRC} = 0.267$, the average federal tax rate for the fifth quintile of income.[18] We set the tax on profits $T_\pi = 0.36$ (following the discussion in Trabandt and Uhlig (2011)).[19]

Depreciation rates We use the annual specific capital depreciation estimated by Eden and Gaggl (2018) and set accordingly $\delta_A = 19\%$ and $\delta_K = 12\%$.

Production function parameters Consistent with the polarization empirical literature, such as Autor, Levy and Murnane (2003) and Autor and Dorn (2013), and the recent optimal robot's tax policy analysis as in Guerreiro, Rebelo and Telels (Forthcoming), we assume 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.[20] Specifically, we assume aggregate output is

[16] This utility function allows for a clean characterization of ability cutoffs, as derived in Appendix A.4. Moreover, we assume that $\eta_j = 1$ as, for technical reasons, it allows for the solution of a quadratic equation in hours worked which simplifies the analysis of the full transition dynamics in the policy experiments below.

[17] To put this into context, the resulting value of steady state consumption of an individual outside the labor force equals to 0.24 of the average wage in the economy. To construct the empirical counterpart we proceed as follows. We look at the sample of individuals aged 18-65 outside the labor force (excluding students and housewives) in the Annual Social and Economic Supplement (ASEC) of the CPS for 2017. We find that the total social assistance transfers (including social security income, welfare (public assistance) income, supplemental security income, income from worker's compensation, income from disability benefits, and market value of food stamps) account for 17% of the average earnings.

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

[19] This calibration implies that there are revenues above and beyond what is required to fund the government transfers; we set those as fixed government expenditures that are not valued by individuals and keep them constant across all our policy experiments.

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

produced via

$$Y_t = K_t^{\gamma} Y_{NRM,t}^{\psi(1-\gamma)} \left[(1-\alpha) Y_{NRC,t}^{\varsigma} + \alpha \left[X_A^{\nu} + Y_{R,t}^{\nu} \right]^{\frac{\varsigma}{\nu}} \right]^{\frac{(1-\psi)(1-\gamma)}{\varsigma}} \tag{5}$$

where ν governs the degree of substitution between R labor and automation capital, and ς governs the elasticity of substitution between the (X_A, Y_R) composite and NRC labor.[21]

The parameters $\psi, \alpha, f_R, f_{NRM}$ also determine various income shares. We normalize $f_{NRM} = 1$. The data moments we use to discipline the remaining three parameters are the income shares (out of GDP) of total labor, routine labor, and the share of automation capital (see below for the description of this capital stock).

Two remaining 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, which controls the elasticity of substitution between Y_{NRC} and the (X_A, Y_R) composite. Our approach is to feed in a proxy for the *observed automation capital price fall* and iterate over ν and ς such that we match two moments: (i) the percentage change in automation capital (i.e., we match the observed elasticity of automation capital to its relative price), and (ii) the split between NLF and NRM in accounting for the decline in R employment propensity among the low-skilled.[22] To do so, we use as our proxy for the decline in automation price, the 1989 to 2017 decline in the price of information and communication technology (ICT) capital as reported in Eden and Gaggl (2018); Over our period of interest this price declined by 68%.[23] 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 U.S. 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.

Hence, our first targeted moment is the estimated elasticity of ICT to its price over this period from Eden and Gaggl (2018), which is (-1.67). For our second data moment we use CPS data as in Section 2, averaged over men and women, and find that, within low-skill non-NRC workers, 65% of the decline in R employment is accounted for by non-participation and the rest by reallocation to NRM. While we cannot establish a causal link between automation and the share of the decline in R accounted for by non-participation, the model revolves around both the occupational choice and the labor participation margins.

[21] 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.

[22] As a robustness check, we also calculate the same moments in the model, using small changes to the price of automation. The calibrated parameters are quantitatively similar.

[23] We note that the estimates in Eden and Gaggl (2018) end in 2013. To extend the series until 2017 we employ two different methods. First, we extrapolate the ICT price and capital series until 2017 based on their median growth rate during the post-Great Recession period. Second, as an alternative method, we note that 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, so we can use its growth rate for the 2013-2017 period (See https://fred.stlouisfed.org/series/B679RG3Q086SBEA) to extrapolate the missing years. Both methods generate almost identical series.

As such we choose to target this moment.[24]

4.1. The allocation and welfare impact of automation

Our goal in this section is to establish that the model is empirically relevant for evaluating automation-related policy instruments. To do so, we demonstrate that the model captures key features of the macroeconomics of automation in recent decades along different dimensions. We report the results in Appendix A.6 and provide a brief summary here.

Our first variable of interest is the decline in routine employment. Naturally, there are other forces that affect it, such as globalization and trade (see for example Autor, Dorn and Hanson (2015)). Hence, we would not expect the decline in the price of automation to explain the entire decline in routine employment. Indeed, the model economy reduces the likelihood of the low-skilled working in R by 10 percent, thus the model, when solely driven by the ICT price change, accounts for more than half of the 17 percent unconditional fall observed for unskilled men between 1989 and 2017.[25] Our second set of variables of interest is aggregate and occupation-specific labor shares of GDP. As we show in the table, the model is consistent with the observed fall in the aggregate labor share in the U.S. (see, for example, Karabarbounis and Neiman (2013)) and in the change in occupation-specific income shares (see discussion in Eden and Gaggl (2018)).

This analysis enables us to gauge the welfare impact of automation, manifested as a decline in the relative price of automation capital in the model. We calculate welfare as the consumption equivalent change between the two steady states, following the decline in the price. High-skill non-routine cognitive workers are the big winners from automation, since they are both the equity owners in the economy and are complements in their labor input to automation capital; they experience a 27% increase in welfare. By contrast, the biggest losers are those unskilled workers who used to work in routine occupations, as a results of the fall in the wages of these jobs. Some of these workers remained in routine occupations post-automation (and suffered a 9.4% welfare drop), while the relatively low-skilled among them ended up in non-routine manual occupations (3.4% welfare decline) or outside the labor force (4.8% loss in welfare). Workers who used to work in low-skill, low-wage non-routine manual occupations actually gained due to the rise in their wages, seeing a welfare increase of 3%.

[24] We explore alternative calibrations targets for these two parameters, naturally, resulting in slightly different estimates. Importantly, our policy experiments deliver almost identical results under these alternative calibrations; results are available upon request.

[25] Recall that two-thirds of the decline in R is due to a rise in out of the labor force. In the model, leaving the labor force is an endogenous choice due to the decline in the return to work in R. This is consistent, for example, with workers' take-up of disability insurance as an exit strategy from the labor force. For example, see the discussion in Section II.D in Aaronson et al. (2014) and the references therein showing that non-participation due to disability has been edging up.

5. Policy experiments

We use our modeling framework as a laboratory to consider the impact of two sets of policies informed by current policy discussions. Recall that the results in the empirical and in the model sections suggest that a share of R workers ends up out of the labor force and those that remain in it suffer a decline in their wages and welfare. At the same time, the demand for NRM and NRC increases due to automation.

As such, we begin by studying the effects of two programs designed to retrain those harmed by automation.[26] The first one is targeted at those with the lowest skills who ended up outside the labor force. It seeks to improve their non-routine manual ability (in a distributional sense). Then we consider a program targeted at routine workers with relatively high ability that retrains them to perform non-routine cognitive occupations. This second experiment quantifies the effect of a program that provides high-skill routine workers with the equivalent of a four-year college education.

The second set of policies we consider are explicitly redistributive and transfer resources directly to the low-skilled (low-income). They include: (i) the introduction of a universal basic income (UBI); (ii) increased transfers to those outside the labor force; and (iii) changes in the labor taxes levied on the low-skilled. A number of these policies have been discussed in the context of ameliorating inequality and aiding those most negatively affected by automation.

To make the policy experiments comparable, we keep the "dollar value" of the programs fixed, as discussed below. We start all experiments from the (2017) calibrated steady state, apply the policy, and calculate the full transitional path to the new steady state. We then calculate the change in consumption equivalent welfare due to the policy for each experiment. An important goal of the analysis is to evaluate the heterogeneity in the welfare impact of the policies we analyze. To do that, we simulate low-skill individuals, drawing abilities from the pre-policy change calibrated ability distribution. We then solve for their employment, occupational and hours of work choices given prices in each period throughout the transition and in the new steady state. This allows us to calculate change in consumption equivalent welfare conditional on *pre-policy* employment and occupational status, which is essential for documenting the heterogeneous effects of the different policies.

Finally we note that, given the general equilibrium emphasis of the model, each policy must be financed through increased government taxation. Naturally, since Ricardian equivalence does not hold in our model, the specific way the policies are financed matters. Our approach is to finance the programs via changes to the labor income tax levied on high-skill (NRC) workers that have benefited most from automation. This is

[26] Given our interest in policy analysis, we consider only government-sponsored programs and not market retraining opportunities.

consistent with our interest in analyzing the effects of programs targeted at those most adversely affected by automation. At least in some cases, this approach implies increasing the distortion on the labor supply of high-skill workers.

5.1. Retraining programs

5.1.1. NRM retraining program

Our first policy experiment changes the ability distribution of low-skill workers in the face of automation. We consider a change in the marginal distribution of ε_{NRM} ability (leaving the marginal distribution of ε_R unchanged) capturing the idea of training low-skill workers to do non-routine manual work.

We target those out of the labor force (i.e., with ability below both cutoffs ε_R^* and ε_{NRM}^*) in the steady state. The program allows workers to increase their ability in the NRM dimension; after training, treated individuals re-draw their NRM ability from a new distribution characterized by a higher mean, increasing the chances of obtaining high enough ability to participate in the labor force. Following the new draws, those with relatively high ε_{NRM}, would improve their ability sufficiently to induce them to join the labor force and work in an NRM occupation. Others with low ε_{NRM} would remain outside the labor force.

There are two parameters that we need to calibrate in this experiment: the increase in productivity due to retraining and the cost per participant. We rely for both on the closest existing federal program – the Trade Adjustment Assistance (TAA).[27] Our calibration follows the empirical findings in Hyman (2018); his results imply an increase of 14.4% in productivity due to training that comes at a cost per participant of 14.5% of GDP per capita.[28] To evaluate the (ex-ante) maximum increase in labor force participation, we consider applying this retraining scheme to all individuals who are outside the labor force, implying a one-time total cost of 3.4% of GDP.

Table 2 compares the changes between steady states in terms of allocations and the transitions between the different occupations and labor force participation across the two steady states. In general, the retraining experiments we consider below feature several forces at play that lead to increased GDP. Naturally, they raise the labor force participation of the treated group. In addition to the direct rise in labor input, such increases have several general equilibrium effects. First, complementarities between the various factors of production imply that a higher labor force participation of the treated group leads to changes in the demand

[27] This program assists workers in firms hurt by foreign trade and pays for retraining, among other benefits. See for example the 2015 TAA benefits page: https://www.doleta.gov/tradeact/benefits/2015-amendment-benefits.cfm

[28] Hyman (2018) uses a quasi-experimental setting to estimate the impact of TAA on employment and income. Hyman (2018) finds that TAA workers earn $10,256, or about 44% more per year compared to the control group. Hyman evaluates that about a third of this increase stems from productivity (the rest from the rise in employment) and delivers about 14.4% increase in productivity due to training. We employ this number as the shift in the average ability of those who train.

for all other factors of production. Second, the retraining programs increase the supply of a specific type of labor (different across the programs) and create "displacement effects:" the trained individuals compete with incumbent workers in that occupation. Third, it reduces the labor tax distortion faced by skilled workers who finance lower overall transfers to those outside the labor force, resulting, ceteris paribus, in an increase in their labor supply.[29]

The first column of Table 2 describes the results of the NRM retraining program. A direct effect of it is a fall of 4.77% in non-participation. The majority of the new participants work in NRM occupations since their NRM ability improves thanks to the retraining program. At the same time this direct increase is somewhat muted by a displacement effect – the transition from outside the labor force into NRM of 1.96p.p (row 33) due to the retraining program results in a decline in the wage per NRM efficiency unit of 2.16% (row 17). This fall leads to an outflow outside the labor force of incumbent NRM of 0.34p.p (row 31).

The overall increase in the supply of NRM workers contributes to output growth. In addition, given the complementarity of NRM labor with the other factors of production, the rise in NRM employment boosts the returns to investment and the demand for R and NRC labor. As a result, in equilibrium, we observe a rise in both types of capital stock by about 0.5 – 0.7% (rows 21-22), as well as all labor inputs. Finally, because of reduced payments to those outside the labor force, the distortionary tax levied on skilled workers falls (row 14), which leads to a further increase in their hours worked (row 12). Overall, all of these effects amount to about 0.7% increase in GDP (row 13).

Welfare Next we discuss the welfare impact of this retraining program (presented in Table 3). The main beneficiaries are naturally non-participants who, through retraining, move into the NRM occupation. Their consumption equivalent welfare increases by just over 5.7%.

The group that benefits the second most is the high-skilled, who experience a 1.1% rise in consumption equivalent welfare. Three channels account for it. First, reduced transfers to labor force non-participants cut the high-skilled's labor tax rate by about 3.9p.p. Second, the complementarity effects discussed above raise the NRC wage by about 0.7%. And third, profits increase in this economy – recall NRC workers are the equity holders.

Importantly, we note that this welfare calculation includes the cost of training funded by these NRC workers. This is reflected in the tax levied on these workers, which as can be seen in the figures in Appendix A.8, initially increases. Over time, for the reasons discussed above, this tax converges to a *lower* tax than in

[29]The cost of the retraining programs is also levied on skilled workers; financing requires higher taxes levied on the skilled workers during the implementation of the program. This cost is only manifested during the transition to the new steady state and not in steady state comparison. Hence we relegate the discussion of the financing of the programs to the welfare discussion below.

the initial steady state. This implies that for these NRC workers, the welfare increase is much smaller under the full transition calculation as in Table 3 vis-a-vis the solely steady-state based as in Table A6.

With respect to the low-skilled, the welfare of those who were incumbent NRM prior to the experiment falls because of the displacement effect discussed above. The most negatively affected are those with sufficiently high ε_{NRM} who remain in their occupation and suffer a drop in wages and welfare. Of those who leave their NRM occupation, depending on their abilities, some remain in the labor force and transition to the R occupation, while some drop out of the labor force. The welfare of all of them declines, although the magnitudes of the fall vary depending on the transition they experience.

Finally, with respect to incumbent R workers, their welfare, as Table 3 shows, goes down following this retraining policy, even though their wages rise slightly in the steady state. This occurs because, along the transition path, NRC workers initially reduce their labor input due to the higher distortionary taxation levied on them. Indeed, as the figures in Appendix A.8 show, R workers' wages initially decline. These forces are absent when solely comparing steady states; as Table A6 reports, the welfare of R workers increase in this case.

5.1.2. NRC retraining program

Our second policy experiment targets the relatively high-ability routine workers whose wages fall in the face of automation. Specifically, we retrain them to perform NRC occupations. This experiment quantifies the effect of a program that provides high-skill routine workers with the equivalent of a four-year college education.[30]

For comparability, we use the NRM retraining program's overall cost as an anchor for the NRC retraining program and for the remaining of the experiments we consider below; i.e., we ensure that the overall programs' costs are identical.[31] Since this program is more expensive per participant, the number of treated is smaller. We assume the program compares to a four-year college and rely on realistic college tuition costs and graduation rates to calibrate the exercise, which implies that the number of treated is 15 times smaller.[32] Armed with this number we find the routine ability level above which individuals receive the training. [33]

[30]The focus is on high-ability routine workers being as the ones who receive the NRC retraining since lower ability routine workers are less likely to succeed in transitioning to NRC occupations. See Cortes (2016) for evidence consistent with selection on ability in the context of the transition from routine to NRC occupations.

[31]We verify this in an ex-ante sense; i.e., the costs are the same prior to general equilibrium effects. In that sense the government sets a program and a cost and then the equilibrium in the economy takes place.

[32]See for example Vardishvili (2020) whose estimates suggest that the overall cost of college attendance amounts to two times GDP per capita (as a comparison recall that the first retraining program totaled 14.5% GDP per capita). Moreover, not all college attendants actually graduate, and following Vardishvili (2020) we assume that 29% of the treated individuals do indeed become NRC.

[33]The most able routine workers are, in our model, better off remaining routine. As such in assigning the treatment we make

The second column of Table 2 describes the results. As a direct effect of the program, the fraction of high skilled in the population rises (row 11). As with the previous retraining program, this direct increase reduces wages for incumbent NRC workers (rows 18,19) and leads to a fall in hours worked (row 12).

Overall, the supply of NRC labor units increases (row 8), naturally contributing to output growth. In addition, given the complementarity of NRC labor with the other factors of production, the rise in it raises the returns to investment. As a result, in equilibrium, we observe an increase in both types of capital stock, which is especially visible for automation capital because of the high degree of complementarity between NRC workers and automation. Even though this program does not target directly those outside the labor force (as the first program did), it does slightly increase labor force participation. Overall, all of these effects amount to about 0.44% increase in GDP (row 13).

5.1.3. Comparison of retraining programs

Comparing the two experiments (columns 1 and 2 in Table 2), we note that the GDP impact of the first one is over sixty percent greater. Two factors are responsible. First, recall that we keep the *total treatment cost* of both programs identical in the experiments. So, as discussed above, the number of treated individuals in the second program is much smaller. Second, while in the first experiment individuals who were not working join the labor force, in the second one, the first-order effect of retraining concerns already high-ability working individuals. As such the output gains are relatively smaller.

In terms of welfare (see Table 3), the NRC retraining program yields a gain about twice as large. However, this masks substantial heterogeneity in the welfare impact of the two programs across different individuals. Unlike the first retraining program, where low-wage unskilled NRM workers were the major losers, showing decline in welfare, in the NRC retraining program all unskilled workers weakly see an increase in their welfare. The main beneficiaries of the NRC program are naturally those routine workers who, through retraining, move into NRC occupations.[34] Furthermore, the wages and welfare of workers in routine occupations – either those who used to work there or who transitioned there – rise due to the exodus of some routine to NRC occupations, and to complementarities with NRC. Finally, we note that the welfare of even the lowest-skilled NRM workers inches higher because of complementarities in production.

Who loses when new NRC workers are trained? Incumbent NRC workers experience a welfare decline of about 1.06%. This happens despite profits rising in the economy and the distortionary labor tax they

sure that those who receive are indeed better off (we formally discuss their welfare calculation below); technically this identifies two ability cutoffs.

[34]For this group we calculate welfare assuming that equity is held only by incumbent NRC. Given the lack of idiosyncratic uncertainty, this is indeed an equilibrium result.

face falls. Two economic forces drive this welfare decline. First, competition from new NRC workers puts downward pressure on NRC wages. Second, the retraining cost is borne by the NRC during the retraining period.[35]

Table 3: Impact of Policies: Welfare

	(1) Retraining	(2) Retraining NRC	(3) UBI	(4) Increased transfers to NLF	(5) More tax progresivity
R to R	-0.2026	1.3729	0.3232	0.5419	0.4565
R to NRM	NaN	NaN	NaN	NaN	0.5005
R to NLF	NaN	NaN	0.6594	1.4129	NaN
R to NRC	NaN	1.9567	NaN	NaN	NaN
NRM to R	-1.2280	0.9139	0.3603	0.4419	NaN
NRM to NRM	-2.3197	0.3765	0.2974	0.3546	0.5455
NRM to NLF	-1.0455	NaN	0.6480	1.3160	NaN
NLF to R	0.0071	0.7006	NaN	NaN	0.2291
NLF to NRM	5.7162	0.1779	NaN	NaN	0.2734
NLF to NLF	0.0000	0.0000	0.8013	2.3213	0.0000
NRC to NRC	1.0866	-1.0602	-0.4972	-1.3383	-0.3578
Group averages					
Started in R	-0.2026	1.3807	0.3240	0.5556	0.4565
Started in NRM	-2.2852	0.3797	0.2983	0.3702	0.5455
Started in NLF	0.3240	0.0149	0.8013	2.3213	0.0019
Started in NRC	1.0866	-1.0602	-0.4972	-1.3383	-0.3578
Weighted Average	0.0590	0.1365	0.1659	0.3295	0.0984

Notes: Each column represents the welfare effects of the five different policies we consider. To calculate them we first compute the full transition path consumption equivalent welfare. Results are presented in percentage change of these measures vis-a-vis the initial steady state consumption equivalent welfare.

[35] This is why it is imperative in such experiments to account for the full transition between the steady states and not merely to compare two steady states. In comparing the steady state-based welfare in Table A6 vis-a-vis the transition-based ones in Table 3, we note the main differences are visible for incumbent R workers and NRC workers. As is the case in the NRM retraining program discussed above, when taking into account the full transition path, the welfare of these two groups is lower than when steady state comparisons are used. As with the previous retraining program the reason is that along the transition path, initially the NRC workers reduce their labor input by even more than in the steady state, which leads to an initial fall in R workers' wages. For example, when comparing steady states the welfare loss of the NRC incumbents is only about half that than when the full transition is accounted for. We thank the editor and two anonymous referees for highlighting this point to us.

Table 2: Impact of Policies: Allocations

		(1)	(2)	(3)	(4)	(5)
		Retraining	Retraining NRC	UBI	Increased transfers to NLF	More tax progresivity
1	**Cutoffs**					
2	eps_R_star	-0.07	-1.82	0.23	1.81	-0.53
3	eps_NR_star	2.2	-0.65	0.25	2.02	-0.63
4	**Labor states**					
5	Not in the labor force	-4.77	-1.72	0.43	2.97	-0.83
6	Employed in R	0.56	1.09	-0.19	-1.47	0.44
7	Employed in NRM	7.03	0.5	-0.32	-1.79	0.44
8	Y_NRC	0.2	1.04	-0.2	-0.23	-0.08
9	Y_R	0.4	-0.53	-0.29	-0.76	0.1
10	Y_NRM	2.94	-0.21	-0.32	-0.85	0.11
11	Pop_NRC	0	1.28	0	0	0
12	Hours NRC	0.2	-0.24	-0.2	-0.23	-0.08
13	**GDP**	0.72	0.44	-0.24	-0.46	0
14	**NRC Tax**	-3.95	-1.51	2.54	3.92	2.16
15	**Wages per efficiency unit**					
16	Wage R	0.07	1.85	0.09	0.6	-0.21
17	Wage NRM	-2.16	0.65	0.07	0.39	-0.12
18	Wage NRC	0.72	-1.58	-0.1	-0.58	0.2
19	After tax Wage NRC	2.17	-1.04	-1.02	-1.99	-0.59
20	**Capital**					
21	Automation	0.53	2.97	-0.11	0.37	-0.3
22	Non-automation	0.72	0.44	-0.24	-0.46	0
23	Profits	0.71	0.61	-0.24	-0.41	-0.02
24	**Transitions (in Percentage points)**					
25	R to R	45.6	44.99	45.51	44.9	45.61
26	R to NRM	0	0	0	0	0.01
27	R to NLF	0	0	0.11	0.72	0
28	R to NRC	0	0.61	0	0	0
29	NRM to R	0.23	0.12	0	0.02	0
30	NRM to NRM	19.26	19.71	19.78	19.49	19.83
31	NRM to NLF	0.34	0	0.05	0.32	0
32	NLF to R	0.03	0.71	0	0	0.18
33	NLF to NRM	1.96	0.1	0	0	0.09
34	NLF to NLF	32.59	33.77	34.55	34.55	34.28

Notes: Each column represents the allocation effects of the five different policies we consider. Rows 1-23 report percentage changes while rows 25-34 report percentage point changes.

5.2. Redistribution Programs

In our next set of experiments, we look at a broad set of redistribution policies: (i) the introduction of a universal basic income (UBI) modeled as an identical lump-sum transfer to each individual, irrespective of her skill or labor force status; (ii) increased transfers to those outside the labor force who belong to the low-skilled group; and (iii) reduced labor taxes levied on the low-skilled. We emphasize that to make the policy experiments comparable, we keep their total budget costs identical to the retraining programs discussed above.[36]

UBI The UBI program reduces GDP by about one-quarter of a percent (third column of Table 2) as labor force participation, the employment of low-skill workers, and the labor input of the high-skilled decline. This latter group reduces its hours worked since it faces higher distortionary taxation, which is required to fund the UBI transfers. Since NRC labor input is complementary to routine and non-routine manual work, the fall in high-skill labor supply reduces the marginal product of low-skill labor; this reduces the value of labor force participation as reflected in the NLF rise seen (row 5). In addition, the UBI program creates a wealth effect that reduces the supply of hours, conditional on working. Overall, then, introducing UBI increases the value of non-participation and draws workers out of the labor force.

In terms of program's welfare impact, it increases the consumption equivalence welfare of the unskilled while reducing that of the skilled workers who pay for it. Although the high-skilled receive a UBI transfer too, this income increase is more than offset by the drop in their after-tax labor and equity income (as the economy's firm owners) and results in a decline in their welfare.

Out of the Labor Force Transfers This policy experiment increases transfers to those no longer participating in the labor force (fourth column of Table 2). Not surprisingly, it lowers labor force participation. To finance it, the distortionary tax rate on high-skill labor is raised, which leads to a fall in NRC labor input (see row 8). As a result of the decline in both low- and high-skilled labor, aggregate output falls by roughly 0.5%. The fall in the supply of unskilled labor results in a rise in their wages, which in turn increases the amount of automation capital. Hence, this type of transfer in fact accelerates automation, further hurting those routine workers.

In terms of its welfare impact, the program, like UBI, increases the consumption equivalence welfare of the unskilled while reducing that of the skilled workers who pay for these programs. For the low-skilled,

[36]Since the retraining programs are enacted once while the redistribution programs include transfers on a per-period basis, we ensure that the present value of the redistribution programs equals the retraining programs' cost. Hence, while these programs were equal to a one time 3.4% of GDP, their per-period, per capita cost equals 0.13%.

the greatest beneficiaries are those who choose labor force non-participation. Those who remain in the labor force see a modest increase in welfare due to the rise in low-skill wages discussed above.

Tax Reform The previous two policy experiments suggest that there is much room for redistribution. But such transfer programs come at a 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 a smaller output loss and greater labor force participation. Specifically, we consider a more progressive tax system that lowers the labor tax rate, $T_{NRM} = T_R$, that low-skill workers pay.[37]

The fifth and final column in Table 2 reports the effect of this policy. First, in equilibrium, it requires that a higher tax rate be levied on the high-skilled (row 14). Eliminating income taxation on low-skill workers naturally increases the value of their participation, resulting in an increase in their labor force participation. In contrast, the tax increase on the high-skilled reduces their labor supply (row 12), but less than in the cases of the UBI and transfers to those outside the labor force policies. These offsetting changes in employment and labor supply are reflected higher employment of and more hours worked by the unskilled. Overall, we find essentially no impact on aggregate output.

This rise in after-tax wages implies that, in terms of welfare, this experiment delivers gains to the low-skilled who participate in the labor market. But the gains are not reaped disproportionately by those outside the labor force, whose welfare does not increase. Making taxation more progressive favors those who remain in, and elect to join, the labor force. Finally, this experiment also results in smaller welfare losses for the high-skilled relative to the UBI or the increased transfers to non-participants. Why? First, complementarity in production implies that the labor supply rise of the unskilled raises the pre-tax wages of NRC workers. Second, some of the tax increase levied on the NRC is offset by the entry into the labor force and hence the decline in total transfers to those outside the labor force. Such an increase is reflected in a rise in the pre-tax wage of NRC workers (row 18). Overall, the after-tax wage of NRC workers declines less than in the two other redistribution programs (row 19).

5.3. Summary and program comparison

To summarize, we use the model to evaluate the macroeconomic and distributional effects of various public policy proposals. Our two central policies are retraining programs. We find that they increase GDP and labor force participation. However, welfare wise, they have different implications. Those who see their welfare

[37]As before we verify that the reduction in the tax rate leads to a total reduction of collected taxes that equals to the ex-ante increase in government expenses in the previous programs. Maintaining a balanced government budget requires the labor tax rate levied on high-skill workers to be raised.

declining in the unskilled retraining program are the incumbent low wage workers in the NRM occupations. In contrast, in the NRC retraining program, it is the high wage NRC workers who experience a fall in their welfare.

We also look at direct redistribution programs. All low-skill workers (weakly) enjoy an increase in their welfare across these programs, while those who bear the cost of them, NRC workers, experience a decline. The key difference across these redistribution programs is that the UBI and the transfers to those outside the labor force lower GDP and labor force participation; conversely, making the tax system more progressive raises labor force participation, has no impact on GDP, and imposes relatively smaller welfare losses on the high-skilled.

These general insights are robust to alternative calibrations we experimented with, both in terms of the correlation structure between abilities in the model (see the tables in Appendix A.7), and with respect to different calibration approaches that imply somewhat different elasticities of substitution in the production function.[38]

6. Conclusions

We consider the aggregate and distributional impact of various public policy proposals in the face of the dramatic change in the occupational composition of employment due to automation observed over the past four decades. To do so, we develop an empirically relevant heterogeneous agent macroeconomic model with investment in automation capital, labor force participation and occupational choice, and a rich tax-transfer system.

The general equilibrium nature of the model with its emphasis on heterogeneity enables us to conduct and evaluate in a meaningful way the welfare implications of the retraining and redistribution policies we consider. Our framework emphasizes important general equilibrium effects such as (i) complementarities between the various factors of production, (ii) displacement effects of retraining programs, and (iii) the effects on labor supply of changes in distortionary taxation required to fund such programs.

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

[38] Results available upon request.

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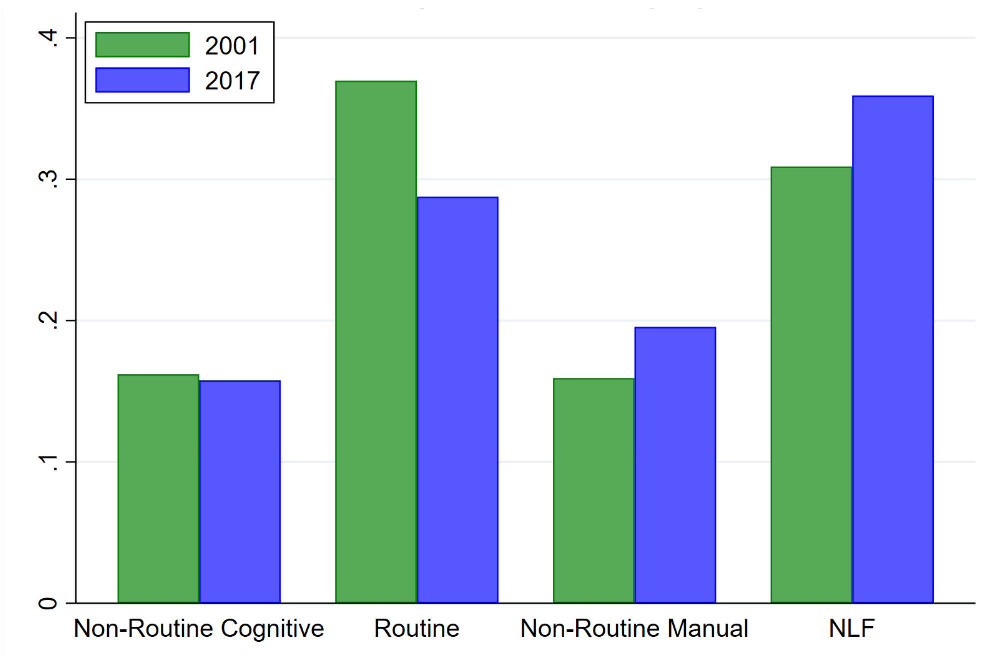
A. Appendix

A.1. Occupation classification

We adopt the occupational classification system used in Jaimovich and Siu (2020) 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. Changes in Employment and Occupational Composition for Low-Skilled Women

Figure A1: Changes in Employment and Occupational Composition for Low-Skilled Women



Notes: Authors' calculations using CPS data for 1989 and 2017. Sample includes all women aged 18 to 65. Low-skilled defined as no college degree. Unemployed counted in their last occupation and unemployment rate is constant within low-skilled between the periods. Share of low-skilled declines from 76% to 70% over the same period.

A.3. 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 A1 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 A2 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 A1: 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 A2: 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.4. Productivity cutoffs

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

A Routine worker with ability ε_R receives an hourly wage equal to the marginal revenue product: $\omega_{R,\varepsilon_R} = f_R P_R \varepsilon_R$, and consumption is simply the wage net of taxes. Therefore the worker's (discounted lifetime) utility is

$$V_{R,\varepsilon} = \frac{1}{1-\beta}\left(\log\left((1-T_R) f_R P_R h_{R,\varepsilon_R} \varepsilon_R\right) - \chi_R \frac{h_R^{1+\eta_R}}{1+\eta_R}\right)$$

With log utility function from consumption we can solve for hours worked using the standard, static consumption-labor optimality condition, where we also note that in this case hours worked are independent of ε_R.

$$\chi_R h_R^{\eta_R} = \frac{(1-T_R) f_R P_R}{(1-T_R) f_R P_R h_{R,\varepsilon_R}}$$
$$\Rightarrow \quad h_R = \left(\frac{1}{\chi_R}\right)^{\frac{1}{1+\eta_R}}$$

Similarly, a NRM worker's discounted lifetime utility is

$$V_{NRM,\varepsilon} = \frac{1}{1-\beta}\left(\log\left((1-T_{NRM}) f_{NRM} P_{NRM} h_{NRM,\varepsilon_{NRM}} \varepsilon_{NRM}\right) - \chi_{NRM} \frac{h_{NRM}^{1+\eta_R}}{1+\eta_R}\right)$$

and hours worked are

$$h_{NRM} = \left(\frac{1}{\chi_{NRM}}\right)^{\frac{1}{1+\eta_{NRM}}}$$

Assuming that all low-skilled workers have the same preferences (i.e. same χ and η) implies that all low-skilled workers work the same number of hours. Therefore, the disutility from work is identical in both occupations, and the worker's choice between the two sectors depend on the occupation where consumption is higher. Specifically, a worker with abilities $\varepsilon = \{\varepsilon_R, \varepsilon_{NRM}\}$ chooses to work in *R* if

$$(1-T_R) f_R P_R h_{R,\varepsilon_R} \varepsilon_R > (1-T_{NRM}) f_{NRM} P_{NRM} h_{NRM,\varepsilon_{NRM}} \varepsilon_{NRM}$$

and because hours worked are identical across the two occupations, the worker chooses to work in *R* if

$$\frac{\varepsilon_R}{\varepsilon_{NRM}} > \frac{(1-T_{NRM})\omega_{NRM}}{(1-T_R)\omega_R}$$

Finally, in order for the worker to prefer working in *R* over non-participation, utility must be larger than the utility from the government transfers that non-participants receive:

$$\frac{1}{1-\beta}\left(\log\left((1-T_R) f_R P_R h_{R,\varepsilon_R} \varepsilon_R\right) - \chi_R \frac{h_R^{1+\eta_R}}{1+\eta_R}\right) > \frac{\log(b_0)}{1-\beta}$$

$$\left(\log\left((1-T_R) f_R P_R \left(\frac{1}{\chi_R}\right)^{\frac{1}{1+\eta_R}} \varepsilon_R\right) - \chi_R \frac{\left(\left(\frac{1}{\chi_R}\right)^{\frac{1}{1+\eta_R}}\right)^{1+\eta_R}}{1+\eta_R}\right) > \log(b_0)$$

$$\log\left((1-T_R) f_R P_R \left(\frac{1}{\chi_R}\right)^{\frac{1}{1+\eta_R}} \varepsilon_R\right) - \frac{1}{1+\eta_R} > \log(b_0)$$

$$\varepsilon_R > \frac{\exp\left(\log(b_0) + \frac{1}{1+\eta_R}\right)}{(1-T_R) f_R P_R \left(\frac{1}{\chi_R}\right)^{\frac{1}{1+\eta_R}}}$$

An analogous term applies for a worker that chooses to work in the NRM occupation.

A.5. Ability distribution parameters

Given the assumptions of the model, we can solve for the standard deviations and cutoffs of the ability distributions, such that we match the labor force share, occupational composition and the observed variance of occupational wages in 2017. Once these are estimated, the rest of the parameters in the model are calibrated to match the different targets discussed in Section 4.[39]

To do so, 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.7.

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 in the routine and non-routine manual occupations in 2017 (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, the log of the routine wage can be written as:

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

where D denotes a constant 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:

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

[39] Thus, this is a sequential calibration process where we first find the ability distribution parameters, and then the rest of the parameters' values depend on the identified ability parameters.

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

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

with a similar expressions for the variance of observed NRM wages. To calibrate the standard deviations, we use the CPS outgoing rotation sample hourly wage for unskilled individuals aged 18 to 65. 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 2017 is 0.4697, while that for NRM equals 0.5284).

A.6. Model Performance

Table A3: Model Performance

	Data	Model
Employment		
% change in routine employment	-17	-10.2
Income Shares (Change in p.p)		
% of GDP: Total	-4.30	-1.88
% of GDP: Routine	-9.51	-5.50
% of GDP: Non-Routine Cognitive	4.17	3.62

Notes: All changes are between 1989 and 2017; see Eden and Gaggl (2018) for income shares. Change in income share of Non-Routine Manual is 0 by construction in the model and is 0.67 p.p in the data

A.7. Alternative calibration of ρ

Table A4: Alternative calibration with $\rho = 0.5$

		(1) Retraining	(2) Retraining NRC	(3) UBI	(4) Increased transfers to NLF	(5) More tax progresivity
1	**Cutoffs**					
2	eps_R_star	0.2	-1.63	0.29	1.9	-0.49
3	eps_NR_star	1.72	-0.83	0.32	2.09	-0.56
4	**Labor states**					
5	Not in the labor force	-4.56	-1.56	0.45	2.93	-0.77
6	Employed in R	0.51	1	-0.23	-1.5	0.38
7	Employed in NRM	6.77	0.41	-0.25	-1.65	0.46
8	Y_NRC	0.22	1.04	-0.2	-0.22	-0.08
9	Y_R	0.59	-0.39	-0.22	-0.66	0.16
10	Y_NRM	2.44	-0.4	-0.21	-0.74	0.21
11	Pop_NRC	0	1.27	0	0	0
12	Hours NRC	0.22	-0.23	-0.2	-0.22	-0.08
13	**GDP**	0.7	0.43	-0.2	-0.42	0.03
14	**NRC Tax**	-3.89	-1.46	2.46	3.79	2.12
15	**Wages per efficiency unit**					
16	Wage R	-0.21	1.64	0.02	0.5	-0.26
17	Wage NRM	-1.7	0.84	0.01	0.32	-0.18
18	Wage NRC	0.78	-1.51	-0.02	-0.49	0.26
19	After tax Wage NRC	2.21	-0.99	-0.92	-1.86	-0.51
20	**Capital**					
21	Automation	0.19	2.7	-0.18	0.27	-0.34
22	Non-automation	0.7	0.43	-0.2	-0.42	0.03
23	Profits	0.67	0.58	-0.2	-0.37	0.01
24	**Transitions (in Percentage points)**					
25	R to R	45.54	45.01	45.64	44.92	45.62
26	R to NRM	0	0	0	0	0.01
27	R to NLF	0.08	0	0	0.72	0
28	R to NRC	0	0.61	0	0	0
29	NRM to R	0.31	0.17	0.01	0.04	0
30	NRM to NRM	19.29	19.67	19.8	19.49	19.79
31	NRM to NLF	0.23	0	0	0.29	0
32	NLF to R	0	0.62	0	0	0.19
33	NLF to NRM	1.87	0.11	0	0	0.08
34	NLF to NLF	32.67	33.81	34.56	34.55	34.32

Notes: These columns report the allocation effects under an alternative calibration of $\rho = 0.5$

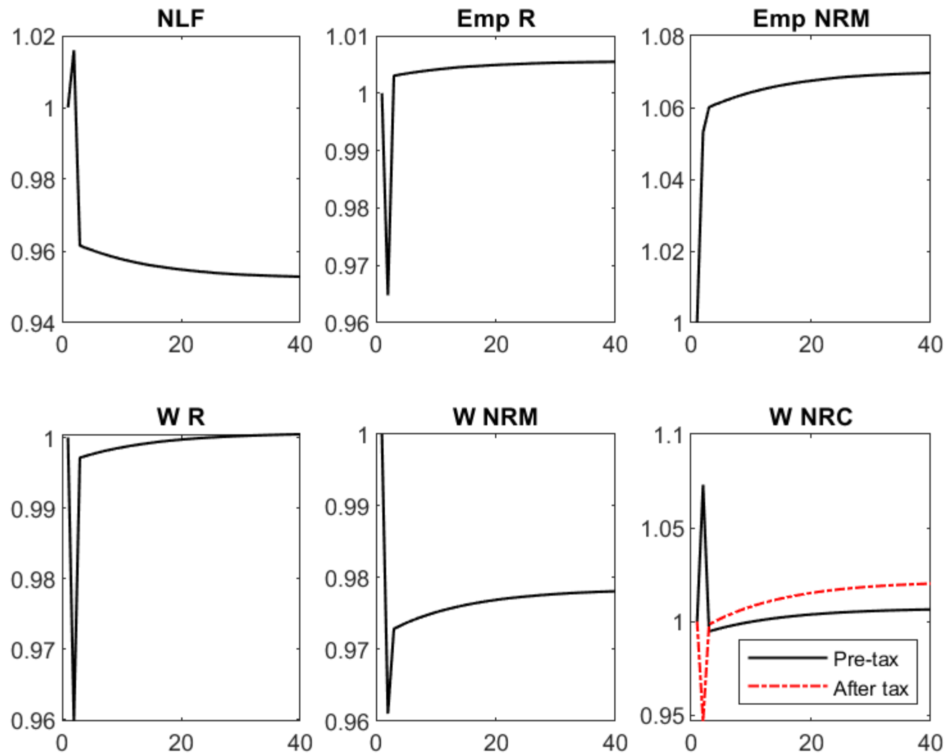
Table A5: Alternative calibration with $\rho = -0.5$

		(1)	(2)	(3)	(4)	(5)
		Retraining	Retraining NRC	UBI	Increased transfers to NLF	More tax progresivity
1	**Cutoffs**					
2	eps_R_star	-0.23	-1.87	0.28	1.78	-0.46
3	eps_NR_star	3.01	-0.31	0.3	1.99	-0.56
4	**Labor states**					
5	Not in the labor force	-5.17	-1.91	0.5	3.2	-0.85
6	Employed in R	0.52	1.13	-0.26	-1.6	0.41
7	Employed in NRM	7.81	0.73	-0.29	-1.91	0.55
8	Y_NRC	0.22	1.08	-0.2	-0.23	-0.07
9	Y_R	0.36	-0.5	-0.23	-0.75	0.19
10	Y_NRM	3.91	0.24	-0.23	-0.83	0.24
11	Pop_NRC	0	1.3	0	0	0
12	Hours NRC	0.22	-0.22	-0.2	-0.23	-0.07
13	**GDP**	0.87	0.55	-0.21	-0.46	0.05
14	**NRC Tax**	-4.45	-1.84	2.48	4.01	1.99
15	**Wages per efficiency unit**					
16	Wage R	0.24	1.92	0.05	0.59	-0.29
17	Wage NRM	-2.92	0.31	0.02	0.38	-0.19
18	Wage NRC	0.85	-1.49	-0.04	-0.56	0.28
19	After tax Wage NRC	2.49	-0.83	-0.94	-2.01	-0.45
20	**Capital**					
21	Automation	0.81	3.13	-0.14	0.36	-0.35
22	Non-automation	0.87	0.55	-0.21	-0.46	0.05
23	Profits	0.87	0.72	-0.21	-0.41	0.02
24	**Transitions (in Percentage points)**					
25	R to R	45.62	45	45.63	44.91	45.63
26	R to NRM	0	0	0	0	0
27	R to NLF	0	0	0	0.73	0
28	R to NRC	0	0.62	0	0	0
29	NRM to R	0.15	0.08	0	0.01	0
30	NRM to NRM	19.16	19.78	19.81	19.43	19.78
31	NRM to NLF	0.54	0	0	0.37	0
32	NLF to R	0.09	0.78	0	0	0.19
33	NLF to NRM	2.2	0.06	0	0	0.1
34	NLF to NLF	32.23	33.69	34.56	34.54	34.29

Notes: These columns report the allocation effects under an alternative calibration of $\rho = -0.5$

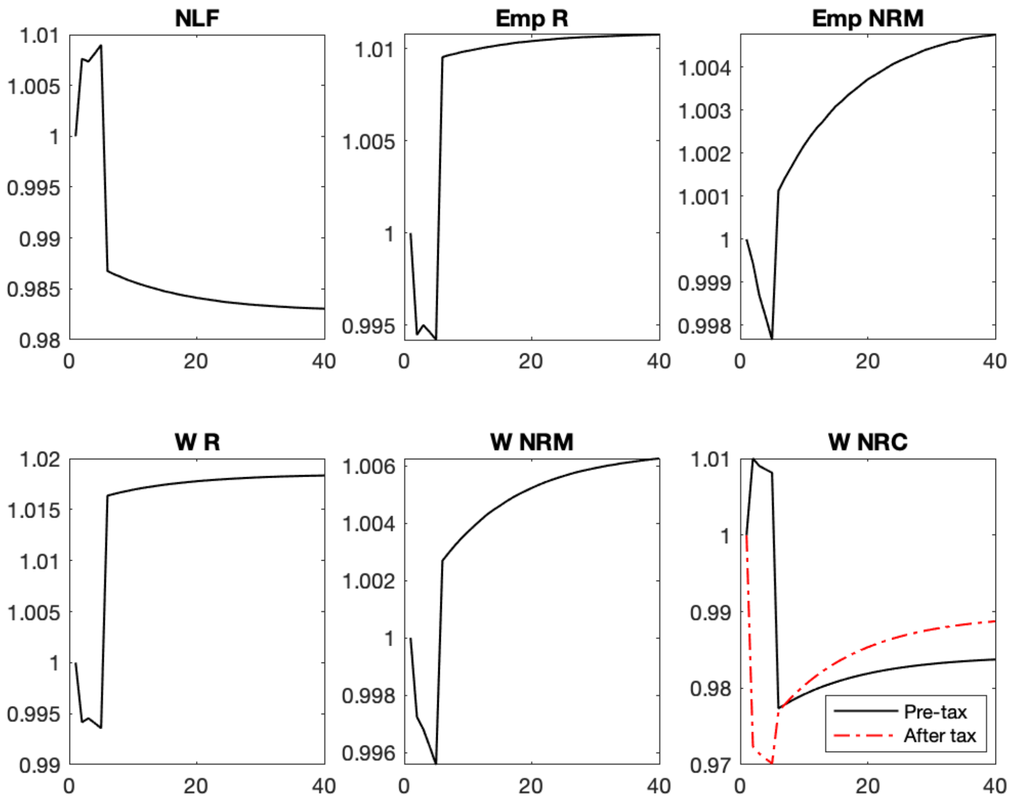
A.8. Transition dynamics

Figure A2: Transition dynamics: NRM retraining program



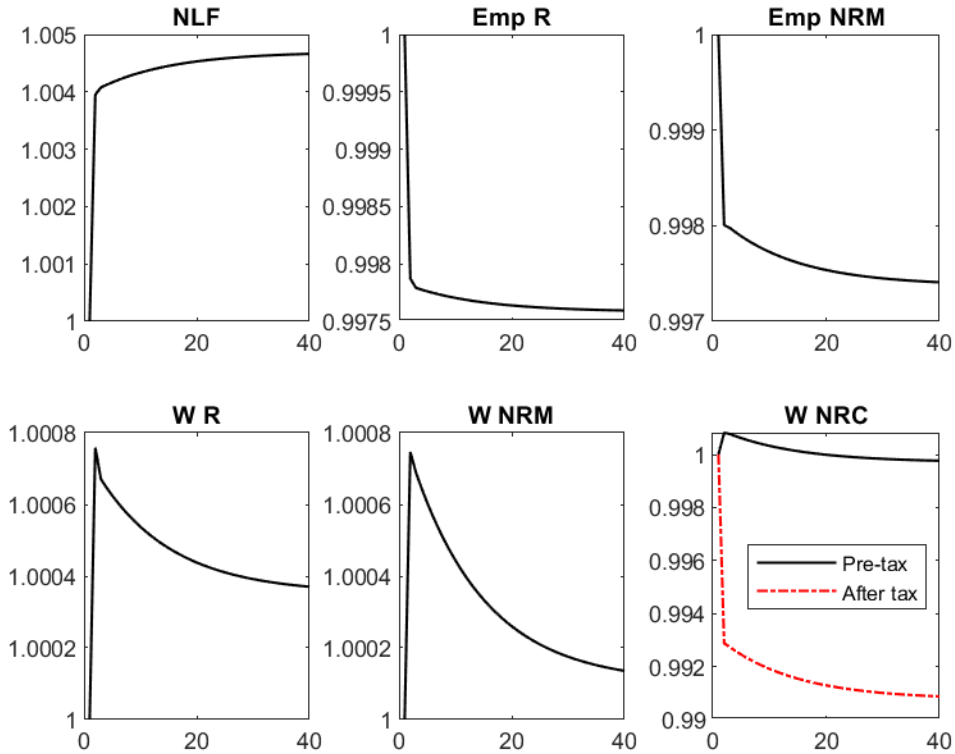
Notes: values for the initial steady state are normalized to 1.

Figure A3: Transition dynamics: NRC retraining program



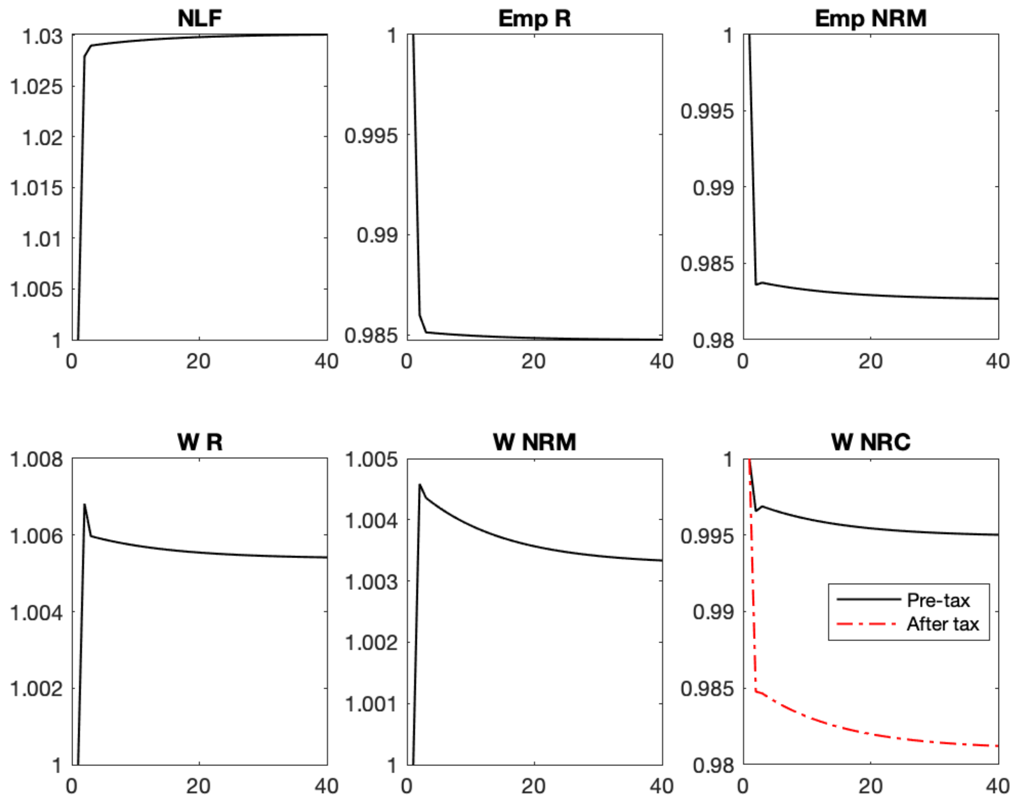
Notes: values for the initial steady state are normalized to 1.

Figure A4: Transition dynamics: UBI



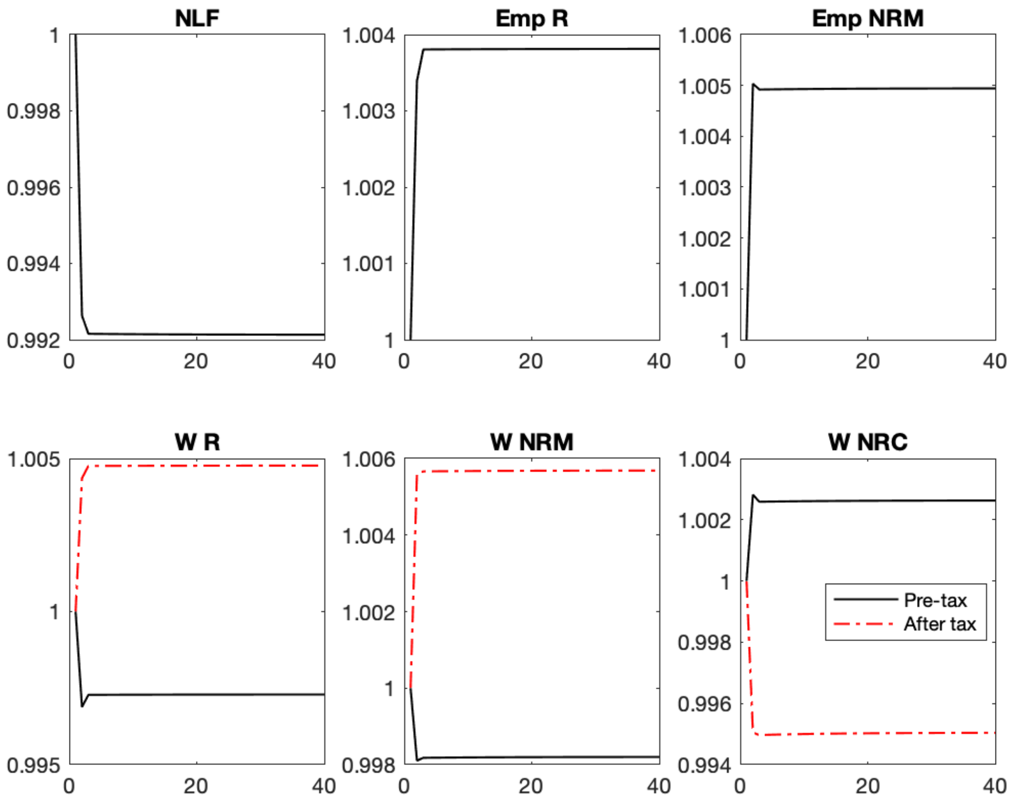
Notes: values for the initial steady state are normalized to 1.

Figure A5: Transition dynamics: increasing transfers to NLF



Notes: values for the initial steady state are normalized to 1.

Figure A6: Transition dynamics: more tax progressivity



Notes: values for the initial steady state are normalized to 1.

Table A6: Impact of Policies: Steady State Welfare

	(1) Retraining	(2) Retraining NRC	(3) UBI	(4) Increased transfers to NLF	(5) More tax progresivity
R2R	0.0672	1.8489	0.3238	0.5381	0.4768
R2NRM	NaN	NaN	NaN	NaN	0.5217
R2NLF	NaN	NaN	0.6854	1.4694	NaN
R2NRC	NaN	2.9509	NaN	NaN	NaN
NRM2R	-1.0500	1.2469	0.3587	0.4330	NaN
NRM2NRM	-2.1558	0.6529	0.2871	0.3271	0.5685
NRM2NLF	-1.0871	NaN	0.6725	1.3682	NaN
NLF2R	0.0343	0.9239	NaN	NaN	0.2402
NLF2NRM	6.2213	0.3267	NaN	NaN	0.2855
NLF2NLF	0.0000	0.0000	0.8334	2.4153	0.0000
NRC2NRC	1.8051	-0.6261	-0.5861	-1.5197	-0.3691

Notes: Each column represents the steady state welfare effects of the five different policies we consider, when not considering the transition path.