Technological Change and Demand for Redistribution: Micro Evidence and Macro Implications

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Abstract

I study the role of technological change in explaining rising income inequality and non-increasing progressive taxes from 1978 to 2018. I first document that an increase in tasks requiring the use of a computer is salient in higher-paying occupations. Next, I link occupational-level data with individual responses on preferences for redistribution and document that occupations that experienced the largest increases in computerization also experienced larger declines in preferences to redistribute income. This computerization effect is significant and sizeable even controlling for occupational earnings. To rationalize this finding, I develop a tractable quantitative general equilibrium political economy model embedding technological change. In the model, workers more exposed to computerization have more to gain from skill investment, and thus are more hurt by more distortive taxes. Therefore, they are more opposed to progressive taxation. The quantitative model features multiple types of tasks, equipment, occupations, and demographic groups where workers consider college education before entering the labor market, select occupations based on comparative advantage, and vote for a redistribution policy modeled as the progressive tax system. In an estimated version of the model that matches the linked micro data, I find that a decline in equipment prices leads to an increase in income inequality, while tax progressivity is non-increasing. If workers' skill accumulation were not allowed during the technological change, the model generates an increase in tax progressivity.

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1 Introduction

Advancement of technology is at the heart of economic prosperity and is a key to achieve better standard of living in a society as a whole. Nonetheless, the past several decades have seen a surge in income inequality in the United States, and biased technological change has been considered a culprit of the widening gap (e.g., Katz and Murphy (1992)). For example, a sharp decrease in equipment prices since the 1970s has been considered one of the main drivers of the elevating inequality (e.g., Greenwood et al. (1997); Krusell et al. (2000)).

Despite the surge in inequality, empirical studies have documented that the progressivity of government tax and transfer has either decreased or changed little so far in the US (Piketty and Saez (2007); Slemrod and Bakjia (2017); Heathcote et al. (2020); Saez and Zucman (2020)). Provided that progressivity is a degree of government redistribution, these trends in rising inequality and less government redistribution are puzzling.[1] The aim of this paper is to reconcile these puzzling trends: non-increasing progressivity and rising inequality.[2]

This paper studies the role of computerization in explaining rising income inequality and non-increasing tax progressivity through a shift in redistribution preferences of workers across occupations from 1978 to 2018. This paper adds to the literature by documenting how technological change measured at the task level affects preferences for redistribution. I answer these questions with individual responses on preferences for redistribution, skill contents, and labor market outcomes data linked at the occupation level. These linked data include socio-political opinions of individuals in hundreds of occupations and demographic attributes, as well as tasks that they perform, and tools and technologies used at the workplace.

I first use these data to document that an increase in tasks requiring the use of a computer and social skills is salient in higher-paying occupations, while an increase in tasks requiring manual and routine work is concentrated in lower-paying occupations. I then use these linked data to estimate the impact of computerization on preferences for government redistribution. These preferences are measured from nationally representative US residents' answers to the questionnaire asking their preferences to redistribute income via government taxes. I find that the decline in these preferences is due to computerization. Surprisingly, I find that this

[1]There is a large literature on the link between inequality and redistribution. The widely used positive framework (e.g., Meltzer and Richard (1981)) predicts that a widening inequality would lead to more redistribution, as politicians respond to the majority of poor, given that income distribution is skewed.

[2]In spite of the apparent incongruence, only a handful of studies attempt to offer theoretical explanations about potentially lower redistribution demand despite a widening income gap in a stylized setting (e.g., Bénabou and Ok (2001), Bénabou (2005)) or empirical evidence of potentially counteracting forces against redistribution (e.g., Karabarbounis (2011), Kuziemko et al. (2015)). Except for a very few (Heathcote et al. (2020)), however, there is little quantitative work that integrates a model with data that allows researchers to gauge the substantive effects of potentially competing channels. This paper not just propose a new mechanism, but also fills this gap.

computerization impact is significant and sizeable even controlling for occupational earnings.

I provide an explanation for this novel finding from data through workers' motives for skill accumulation and derive its macroeconomic implications. For this purpose, I develop a first tractable quantitative general equilibrium political economy model embedding technological change. In the model, workers who are more exposed to computerization have more to gain from skill investment, and thus they are more hurt by more distortive taxes. Therefore, these workers are more opposed to progressive taxation. The fully-fledged quantitative model features multiple types of tasks, equipment, occupations, and demographic groups where workers consider college education before entering the labor market, select occupations based on comparative advantage, and vote for redistribution policy modeled as the progressive tax system. The economic block of the model is built on the general equilibrium task-based approach (e.g., Autor et al. (2003); Acemoglu and Autor (2011); Autor and Dorn (2013)), and the multi-sector assignment framework (e.g., Heckman and Sedlacek (1985); Atalay et al. (2018); Burstein et al. (2019)) following the long-standing tradition of Roy (1951). The political block of the model is an extended version of the canonical probabilistic voting theory (Lindbeck and Weibull (1987); Dixit and Londregan (1996)) in which I extend the theory by allowing the political process to be estimable. I then estimate the quantitative model using the linked micro data ranging from skill contents to economic and social policy preferences (e.g., redistribution preferences, political spectrum, abortion, and environmental protection) to the tax and transfer information at the individual level simulated through the NBER TAXSIM based on demographic characteristics and actual US fiscal rules.

To the best of my knowledge, this paper provides the first direct evidence of the technological change effect on redistribution preferences by linking data of individual stated preferences, skill contents, and labor market outcomes at the occupation level. The quantitative theory developed in this paper is the first integration of the canonical political economy with the standard task-based approach and long-run structural change in general equilibrium. In doing so, the model retains tractability that enables not just quantitative exploration under rich heterogeneity but also transparent mechanisms enlightening economic insights.

At the core of the findings are the equity-efficiency trade-off where efficiency concerns are elevated during technological change because of aspiration to acquiring skills during technological change, and the strategic motive through which economic agents are able to influence the policymaking process. On the one hand, an individual exposed to computerization considers it beneficial because of higher returns to skill investment and want to acquire skills. On the other hand, at the group level, computerization widens a gap in the policy stakes of voter groups, within which individuals share common policy interests. From the perspective of policymakers who take an office by being elected, these tensions directly affect their incumbency concern. Therefore, both the equity-efficiency trade-off and the strategic motive are the two qualitatively important pillars in the policymaking process that pins down equilibrium tax progressivity. But, a fully-fledged answer to what extent each of these pillars accounts for the puzzling trends is *a priori* hard to predict. In its essence, therefore, the question is ultimately quantitative.

Through the lens of the estimated model that match the linked micro data, the model predicts that a decline in equipment prices leads to non-increasing tax progressivity but rising income inequality as observed in data, where quantitative performance of the model is remarkable. By conducting counterfactual analyses I find that the equity-efficiency channel accounts for most of changes in rising inequality and non-increasing progressivity. That is, the elevating efficiency concern from skill investment channel during technological change is the key to rationalize the empirical finding and therefore resolve the puzzle. On the other hand, if strategic motives are turned off by modeling a policymaker as if it were the utilitarian planner, the model generates only a slight increase in progressivity.

Related literature This paper contributes to two large sets of literature. First, this paper is directly related to studies of the impact of technological change on labor markets. A vast body of work studies technological change as a cause of rising inequality in earnings between skilled and unskilled workers and observed trends in employment (Katz and Murphy (1992); Krueger (1993); Krusell et al. (2000); Autor et al. (2003); Autor et al. (2008); Acemoglu and Autor (2011); Autor and Dorn (2013), Hershbein and Kahn (2018)). In related recent studies, Atalay et al. (2018) examine how newly introduced technology relates to different task types. Braxton and Taska (2019), and Deming and Noray (2020) study how the rapid introduction of new skill requirements and technology affects the earnings profile of workers in those occupations and the outcomes of displaced workers. This paper contributes to this literature by bridging the impact of computerization and political behavior of workers at the occupation level, and also offers political economic implications through the lens of a quantitative general equilibrium framework that allows for revealing counter-vailing sources and counterfactuals.

The model developed here departs from the existing literature in several aspects. First, I extend a standard task-based assignment model with risk-averse utility, work-leisure trade-off, and fiscal institution featuring a non-linear tax-and-transfer system. Second, the political block of the model is extended to be estimable by adopting specification of political preferences as in Stromberg (2008). In doing so, the model also extends Stromberg's approach by deriving preferences for economic policy as explicitly micro-founded indirect utilities up to policy in contrast to exogenous economic preferences often directly assumed in the literature. Third, the assumption of fixed worker/voter groups in the existing studies is relaxed by introducing the costly college education choice, which shifts the composition of demographic and voter groups. Lastly, the model unifies aforementioned economic and political features while retaining fully non-linear general equilibrium effects via analytical tractability. This tractability not only allows a quantitative exploration of economic and political interactions with rich heterogeneity, but also elucidates underlying mechanisms in a transparent manner.

Second, this paper joins the literature studying determinants of redistribution preferences. Existing studies uses social surveys and highlight socio-political backgrounds, political system and history, culture, and demographic characteristics as determinants of desires for redistribution. In terms of emphasis on economic shocks, Giuliano and Spilimbergo (2014) is closer to this paper. While their study focuses on the impact of rare, large-scale macroeconomic disastrous events on preferences of youth, this paper examines the impact of secular and normal-time, and long-run technological change on preferences of a broad range of individuals, i.e., the near universe of workforce. This paper contributes to the literature by providing evidence between structural change and redistribution preferences.

A growing body of literature increasingly utilizes a broad range of data. For instance, Autor et al. (2020) use various aspects of realized political activity such as media viewership to examine the impact of trade shocks on political preferences. In contrast, this paper uses conventional social survey data in conducting empirical analysis, as in a vast body of existing work (Alesina and Giuliano (2011); Fuchs-Schündeln and Schündeln (2015). Kuziemko et al. (2015), Hvidberg et al. (2020)). This paper contributes to this literature by proposing a novel approach of utilizing well-established sources of data through the pseudo panel method. A merit of this approach is that it allows researchers to explore the relationship of socio-economic factors and changes in preferences for a broad range of questions and time horizons.[3]

Layout The structure of this paper is as follows. Section 2 begins with an introduction to data sources, data linkage, and the empirical analysis of the impact of computerization on redistribution preferences. In section 3, I present a simple model of skill investment and government redistribution that highlights the basic intuition of the empirical result before developing a fully-fledged quantitative model. Section 4 introduces the tractable quantitative general equilibrium political economy model and characterization of the model. Section 5 explains how the model is mapped to the linked micro data. Section 6 discusses the key mechanisms and conducts counterfactual analysis. Section 7 concludes. Appendices contain additional figures and tables of the empirical and quantitative results, and proofs and derivations of the key results in the paper.

[3]For example, this paper uses the pseudo panel approach in pioneering the relationship between redistribution preferences and technological change over nearly the entire course of computerization in the US.

2 Empirical Analysis

2.1 Data overview

I combine multiple data sources to investigate how computerization has affected preferences for government redistribution. Specifically, I use data from the General Social Survey (GSS), Atalay et al. (2020) historical skill content data (hereafter, APST), the Occupational Information Network (O*NET), and standard labor market outcomes from the American Community Survey (ACS), the Occupational Employment Survey (OES), and the Current Population Survey - Annual and Economic Supplement (CPS-ASEC) to conduct my empirical work. Here, I briefly describe public opinion and skill content data and highlight the key variables for the empirical analysis.

GSS The GSS is a socio-political survey that assesses political attitudes, social characteristics, concerns, practices, and experiences of a representative sample of US adult (18+) residents from 1972 onward. This survey is conducted face to face with an in-person interview by the National Opinion Research Center (NORC) at the University of Chicago. The strength of this data set is that it records socio-political information as well as detailed demographic characteristics and occupations. I use the GSS from 1978 to 2018.[4] The sample is restricted for individuals whose ages are between 25 and 64, most of whom completed college education.

Table A1 provides descriptive statistics of the data set. It is balanced in demographics, education attainment, work status, and political attitudes. Hence, the data set is representative and suitable for the purpose of this paper.

APST/O*NET The O*NET is a detailed data source that describes occupations in the United States from a varied set of different dimensions, including their skill content, work context, tools, and technology. The information in the O*NET is collected through individual-level questionnaires that are addressed to both job incumbents and occupational experts. The current form of O*NET was established in 2003, which pertains to 2002 since the O*NET data are released typically twelve to sixteen months after the information is collected. I use vintages that pertain from 2002 to 2018.

The APST data set is on trends in occupational characteristics constructed by transforming the unstructured text of job advertisements or postings in historical newspapers into a

[4]The survey was conducted almost annually with the exceptions of the years 1979, 1981, and 1992. Since 1994, the GSS has been conducted on the biannual basis.

structured database from 1940 to 2000.[5] The data set links job titles to a variety of occupational characteristics, including work styles and contexts, skill and knowledge requirements, and Information and Communication Technology (ICT) usage as in the O*NET. I use their data set from 1978 to 2000.

ACS/OES/CPS-ASEC The ACS is a demographic survey that covers broad, comprehensive information on social, economic, and housing data, conducted by the US Census Bureau. The ACS is designed to provide the information at many levels of geography, including education attainment, income, and employment. I use this information in measuring the occupational wage distribution and employment shares.

The CPS-ASEC is a high-quality source of information used to produce the official annual estimate of poverty and a number of other socioeconomic and demographic characteristics. The strength of this data set lies in the details of its questionnaires (e.g., about more than 50 sources of income, school enrollment, marital status, family structure). In the empirical study, I use this data set to explore alternative hypotheses in the relationship between redistribution preferences and technological change. In estimating the quantitative model, I also use this detailed individual information to simulate net tax liability based on the actual US fiscal rules at the individual level using the NBER TAXSIM 35.

The OES is a semiannual survey and is designed to produce estimates of employment and wages by the 6-digit Standard Occupation Classification (SOC) System. It is the sole data source that contains occupational employment as disaggregated as the O*NET does. I use the OES to construct the relative importance at the 6-digit occupation code to complement the information absent from the O*NET.

2.2 Data linkage

Bridging data sets While all of data sources contain the detailed information at the disaggregated occupation level, a difficulty arises because these data sets use different occupation classifications, and these classifications also change over time.[6] As such, I harmonize first occupation codes in the data sets using David Dorn's 3-digit occupation panel (Autor and Dorn (2013)). The sample size of the GSS in early survey years is much smaller than recent survey years; nonetheless, variables are recorded at disaggregated level. I construct

[5]The dataset is available at https://occupationdata.github.io/. I use their data set which was last updated on May 15, 2019. I appreciate their generosity of making the data set publicly available.

[6]GSS, ACS, and CPS-ASEC are recorded using 3-digit or 4-digit Census occupation classification. APST is recorded at 3-digit Census occupation classification or 6-digit Standard Occupation Code (SOC). O*NET uses its own 8-digit O*NET-SOC Taxonomy.

six broad and twenty intermediate occupation groups to deal with the smaller sample size of the GSS.[7] Table A2 shows the list of these occupations.

Synthetic panel To study how computerization changes individual preferences for redistribution, an ideal source is a panel data set that allows researchers to track the same individual and how this individual's redistribution preferences respond during the course of technological change. As an alternative to achieve this purpose, I construct a synthetic panel from the linked data which consist of three age groups, four tasks, and six broad occupation groups over six time periods.[8] I then standardize the synthetic panel, period by period.[9] To elucidate how task-level technological change affects redistribution preferences differently from earnings, I extract occupational average earnings from the GSS individuals. Other variables in empirical specification included as controls are constructed in the same way.

2.3 Technological change at task-occupation level

In this section, I present the pattern of technological change measured at the task level along the occupational wage distribution from 1978 to 2018.

Measuring computerization In examining the relationship between computerization and redistribution preferences the first and foremost challenge is to measure the pace at which occupations are increasingly computerized over time from the onset of computerization, tracing back to the 1970s.[10] For this purpose, I develop a new way to measure computerization by using the information in skill content data. Specifically, I create a com-

[7] In the 1970s and 1980s, for example, the size of the GSS sample ranges from 300 to 400 individuals and records their occupations using the Census occupation classification, in which the number of occupations is greater than 300.

[8] The linked data include GSS, APST, O*NET, OES, ACS, and CPS-ASEC. Age groups of the synthetic panel are defined as 25-37, 38-50, 51-64, and the six periods are 1978-1986, 1987-1993, 1994-2000, 2001-2008, 2009-2014, and 2015-2018. Tasks include computer, social, manual, and routine. The list of occupation groups is at Table A2.

[9] This period-by-period standardization is for two reasons. First, since the skill content part of the synthetic panel combines two different sources, APST/O*NET, standardization across all periods would not reflect that two data sets are built from different samples. Second, while APST is constructed from job advertisements in newspapers and variables are continuous, O*NET is qualitative data set, which is constructed from questionnaires asking for answers among discrete choices. Standardization offsets this inherent difference and puts measures from two datasets in the same unit.

[10] Measuring computerization for long periods is known to be difficult. In a recent attempt, Burstein et al. (2019) use the Current Population Survey - Computer and Internet Use Supplement that provides the computer usage at work measured with clear and consistent definition over time, but this data set was discontinued after 2003. While there is large literature on using skill contents, the studies mostly focus on certain types of tasks (e.g., cognitive, manual, routine, or interpersonal), which do not directly speak to computerization.

posite measure of tasks requiring the use of a computer by combining (1) Computers & Electronics Knowledge Requirement and (2) Working with Computers questionnaires in the APST/O*NET.[11]

To examine how redistribution preferences are affected at different dimensions of technological change, I also construct social, manual, and routine task intensity measures in accordance with the standard definitions in the literature (e.g., Acemoglu and Autor (2011), Deming (2017)). On the one hand, Deming (2017) studied a mechanism behind the growing importance of social skills and complementarity with cognitive skills. Behind this complementarity, he points out that social skills have been increasingly important since the more powerful computer is available, the more complex problems individuals equipped with cognitive skills are able to solve with the aid of computers. This requires workers to be able to interpret and communicate more complex problems. On the other hand, it is well known in the literature that workers who mainly perform tasks that are codible and routinizable by computers or easily replaced by machines lose their strength in the labor market (e.g., Autor et al. (2003); Acemoglu and Autor (2011)).

Changes in task intensity In an effort to construct consistent task intensity measures across APST and O*NET, I standardize task intensity measures and take a difference of them measured in 1978 and 2018. By construction, the result is a measure of relative changes in task intensity within occupations, which measures the speed of technological change.[12]

Figure 1 plots the technological change measured at task level along with the occupational median wage distribution. An increase in computer and social task intensity has been concentrated in higher paying occupations. In contrast, an increase in manual and routine task intensity has taken place in lower paying occupations. Taken together, the results show non-neutral computerization at the task-occupation level.[13]

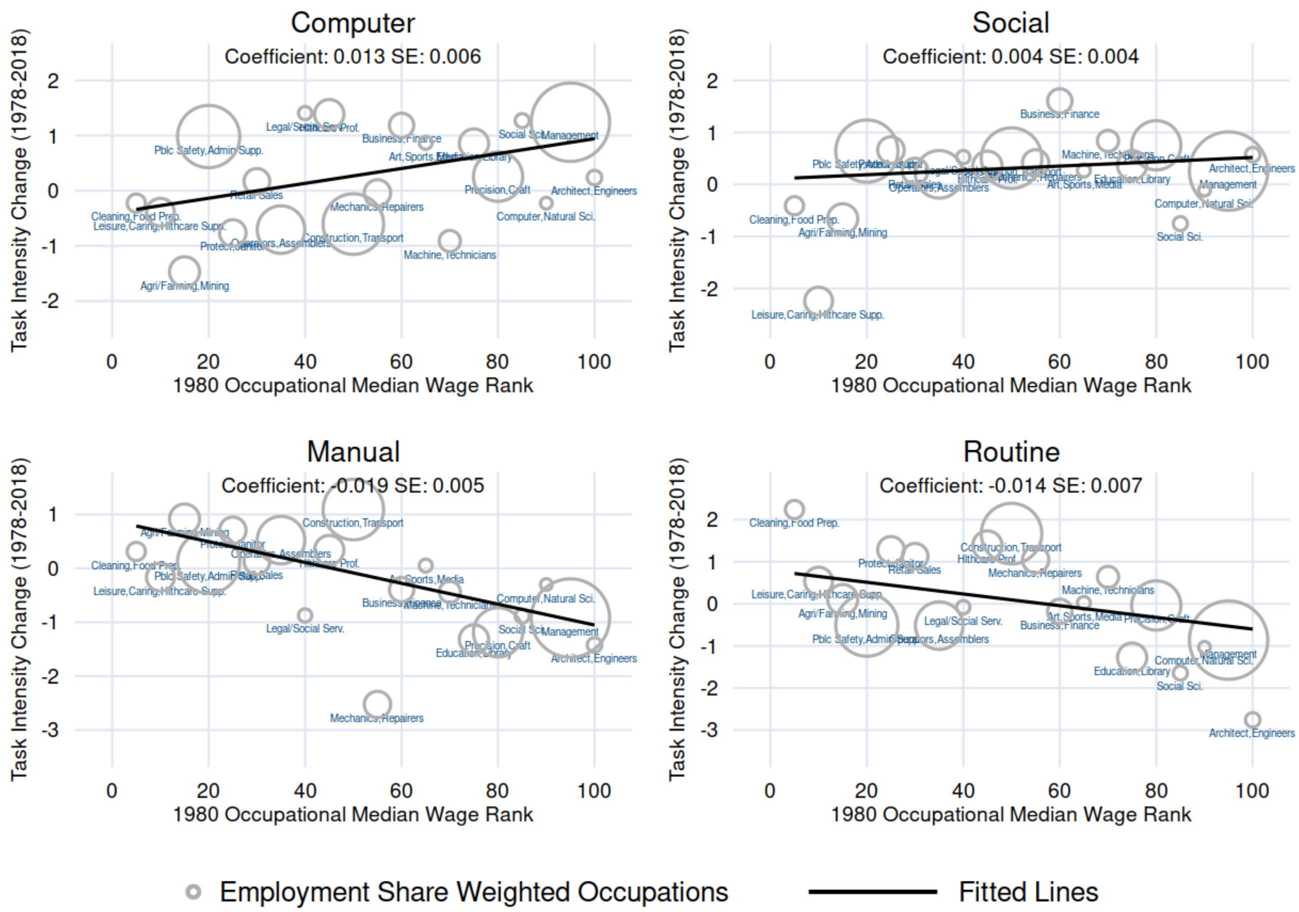
With regard to redistribution preferences, Figure 1 could imply several channels. At first glance, the pattern of technological change would lead to polarized preferences of incumbent

[11] Exemplary occupations with higher computer task intensity include software developer, architect, economist, broadcast technician, etc. Occupations that have shown a rapid increase in computer task intensity from 1978 to 2018 include medical scientists, physicians, social scientists, etc.

[12] Because of standardization, task intensity in an occupation is *relative* to all of the other occupations. Taking a difference of standardized measures between 1978 and 2018, the technological change measure is similar to double-differencing, which measures the *curvature* of task intensity change between 1978 and 2018.

[13] In the literature of task-based approach, existing studies mostly examine task composition at a specific time period or for a limited time horizon due to data limitation. For example, Autor and Dorn (2013) report non-monotonic changes in wage and employment along the occupational wage distribution and its relation to task contents as of 1980 using the Dictionary of Occupation Titles. Deming (2017) uses the O*NET and examines for a time horizon, but the period is limited after early 2000s. This paper corroborates and extend further their implications *over time* as well as for a *longer* time horizon.

Figure 1: Technological Change along the occupational wage distribution



*Notes: Clockwise panels display (x-axis) the changes in task intensities of computer, social, routine, and manual skills, respectively, measured from Atalay et al.'s (2020) and the O*NET-OES merged data (y-axis) along the occupational median wage distribution in 1980 measured from American Community Survey. The slope of regression lines indicates whether the changes in task intensities between 1978 and 2018 have been concentrated in higher or lower paying occupations. Size of circles indicate the relative importance of occupations measured by job posting shares from Atalay et al.'s (2020) data set, and occupational employment shares from O*NET-OES merged data. For the results at the 3-digit occupation level using David Dorn's code see Figure A1.*

workers across *winners* and *losers*. On the one hand, non-neutral technological progress may mean there will be winners and losers in the labor market due to differential gains. For example, computer scientists in 1980 would observe that an increase in computer task intensity is concentrated in higher paying occupations and expect higher market returns in the labor market, which would lead to a reduction in their desires for government redistribution.

The channel above is, however, merely one possibility if workers' skill composition is assumed to be fixed over time. For simplicity, consider a juvenile who is yet to enter the labor market and considers whether or not to attend college. Anticipating the increasing use of computers in the future labor market, he/she may want to attend college if this investment raises his comparative advantage in the labor market. Likewise, incumbent workers in the labor market could also change their skill composition through, for example, on-the-job learning-by-doing or attending retraining programs.

In sum, an individual who can invest in his or her own human capital is faced with the trade-off between wanting more redistribution versus investing more in his or her human capital. If the group of these individuals benefited by technological change is large enough to outweigh the other groups consisting of individuals who are strictly better off by government redistribution, technological progress can lead to a decrease demand for redistribution in aggregate. The results at the disaggregated 3-digit level is available in Figure A1, in which patterns are consistent with those in Figure 1.

2.4 Technological change and redistribution preferences

Measuring demand for redistribution The key variable for my empirical analysis is a measure of preferences for government redistribution against income inequality as a dependent variable. As a measure for these preferences I use the answer to the GSS question:

> "Some people think that the government in Washington ought to reduce the income differences between the rich and the poor, perhaps by raising the taxes of wealthy families or by giving income assistance to the poor. Others think that the government should not concern itself with reducing this income difference between the rich and the poor. Here is a card with a scale from 1 to 7. Think of a score of 1 as meaning that the government ought to reduce the income differences between rich and poor, and a score of 7 meaning that the government should not concern itself with reducing income differences. What score between 1 and 7 comes closest to the way you feel?"

I coded this variable so that a higher number indicates more demand for redistribution and a lower number means less demand. This variable is named "*redistribution preferences*."

2.4.1 Empirical strategy

This section introduces the main empirical strategy and explores the impact of computerization on redistribution preferences using the synthetic panel of group (a, o) over time (t) from the linked data. The main empirical specification I explore is

$$\text{Redist}_{aot} = \beta \text{Task Intensity}_{ot} + \eta_t X_o^{'} \delta + X_{ot}^{'} \lambda + \gamma_a + \eta_t + \gamma_a \times \eta_t + \epsilon_{aot} \tag{1}$$

where on the left-hand side Redist_{aot} is redistribution preferences of synthetic cohort (a, o) in time t, and on the right-hand side $\text{Task Intensity}_{ot}$ is task intensity in occupation o in time t. Therefore, β is the coefficient of interest and it measures how occupational exposure to technological change affects redistribution preferences. I explore different permutations of this specification with task types and occupational earnings.

The time-invariant occupation-specific characteristic is the occupation-specific share of individuals whose political spectrum is reported liberal, which is found correlated with the task intensity measure. I interact it with time to control for pre-trends and other two-way occupation-time shocks.

The time-varying occupation-specific characteristic is job advertisement and employment shares used when constructing occupation groups from the 3-digit Dorn's code, and it is controlled for in order to purge effects of changes in them on the redistribution preferences.

The age fixed effect controls for any age-driven impacts (e.g., potential experience in the labor market). The time fixed effect controls for any common, aggregate changes such as economic and political movements (e.g., business cycles, elections). Interaction of age and time fixed effects is included to control for two-way age-time shocks.

Statistical inference In a statistical inference viewpoint, the task intensity is the generated regressor, in which standard robust inference methods (e.g., the White/Newey-West estimator) fail to deliver consistent variance estimation in general. Moreover, the number of groups in the synthetic panel, $3 \times 6 = 18$, is less than a recommended number of at least 50 clusters for the standard cluster-robust variance estimation. Both issues typically lead to over-rejection of zero-coefficient null hypotheses (i.e., committing a type-one error). To overcome this statistical problem, I estimate confidence intervals using the wild cluster bootstrap method (Cameron et al. (2008); Cameron and Miller (2015)) and clustering is performed at synthetic groups.

2.4.2 Empirical result

Table 1 shows that technological change had an economically and statistically meaningful impact on preferences for government redistribution against income inequality.

Table 1: Redistribution Preferences and Occupational Exposure to Computerization

	Redistributive Preferences (Standardized): 1978-2018 - Synthetic Panel				
	(1)	(2)	(3)	(4)	(5)
Earnings (Occ. Avg.)		**-0.389*****			
		[-0.667,-0.113]			
Computer	**-0.549*****	**-0.312****	**-0.524*****		
	[-0.702,-0.437]	[-0.454,-0.113]	[-0.715,-0.376]		
Social			-0.076		
			[-0.228,0.106]		
Manual				0.057	
				[-0.282,0.371]	
Routine					0.065
					[-0.192,0.319]
Observations	108	108	108	108	108

Notes: The table shows regression results from the estimation of equation 1. Confidence intervals are estimated using the wild cluster bootstrap method, and clustering is performed at synthetic panel groups. Controls include the occupational fraction of individuals whose political spectrum is reported liberal, occupational job posting share, occupational employment share. Fixed effects include age, year, and interaction of age and year in the synthetic panel. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The first and second columns report the results for the main specification with and without occupational average earnings included as a control. Without controlling for occupational average earnings, a one standard deviation increase in computer task intensity reduces redistribution preferences by -0.549 standard deviation.

In column two both occupational average earnings and computerization are included to examine whether the effect on preferences is mainly due to occupational gains in earnings. The gains from higher occupational earnings reduce redistribution preferences. With controlling for occupational average earnings, computerization effect is statistically different from zero and the magnitude of the coefficient is sizeable relative to that in the first column.

The third column includes social and computer tasks. Deming (2017) points out that social skill has been increasingly more important because more powerful computers allow for solving increasingly more complex problems, and this computerization leads to interpreting and communicating with complicated and abstract results being a key to success in the labor market. This implies that social skills would have similar effects as computerization, and if it were the case, the impact of social skills would be overlapped with computerization impact. As such, I test how social skills affect redistribution preferences while computer task intensity is included as a control. The point estimates of social skills are not significant and their maginitude is quite different from computerization, though the sign of social skills is negative as computerization has. The magnitude of the computer task intensity is comparable to that in the first column, confirming Deming's point that the growing importance of social skills would be partly due to computerization.

The fourth and fifth columns investigate whether redistribution preferences are affected by an increase in manual and routine tasks, which has been concentrated in lower paying occupations. The results in both columns report that point estimates are not just statistically significant, but also that their magnitudes are far from the computerization impact.

2.4.3 Competing hypotheses

The previous section provides evidence that redistribution preferences have responded to technological change. This section examines some channels that may explain why preferences may change. I walk through several channels. First, I examine whether changes in occupational share of female workers affect redistribution preferences (e.g., Mulligan and Rubinstein (2008); Cortes et al. (2021)). Second, I explore whether an increase in occupational share of college educated workers affect these preferences. This tests whether education-biased technical change (e.g., Katz and Murphy (1992)) has the similar effects as computerization. Lastly, I investigate whether changes in average worker age shift attitudes toward government redistribution against income inequality, given that changes in worker ages reflect changes in accumulated experience. All variables are measured from the CPS-ASEC. I specify

$$\text{Redist}_{aot} = \beta \text{Alternative Channels}_{ot} + \eta_t X_o^{'} \delta + X_{ot}^{'} \lambda + \gamma_a + \eta_t + \gamma_a \times \eta_t + \epsilon_{aot} \tag{2}$$

Table 2 shows how these alternative forces had an economically and statistically meaningful impact on preferences for government redistribution.

Columns one, two, and three report the result for changes in occupation-specific share of college-educated workers. The first column shows the sole effect of college education and its effect is large and significant. In the second column, however, when occupational average earnings is included, it is no longer significant. In the third column, both education and computer task are included, and the result shows that the coefficient on computer task is significant and similar to the first column.

In the fourth column computer task and occupational share of female workers are included together. The result reports that an increase in female worker share raises redistribution preferences. This effect is consistent with the well-known finding in the GSS studies, stating that females are more supportive of redistribution than males (Alesina and Giuliano (2011);

Table 2: Redistribution Preferences and Occupation Exposure to Alternatives

	Redistributive Preferences (Standardized): 1978-2018 - Alternative Hypotheses				
	(1)	(2)	(3)	(4)	(5)
Earnings (Occ. Avg.)		**-0.783*****			
		[-1.087,-0.418]			
College	**-2.545*****	0.656	-0.403		
	[-4.005,-0.975]	[-0.793,2.771]	[-1.236,0.566]		
Computer			**-0.506*****	**-0.571*****	**-3.912****
			[-0.651,-0.388]	[-0.707,-0.439]	[-8.016,-0.121]
Female				**1.170*****	
				[0.233,2.171]	
Age (Occ. Avg.)					**-0.405****
					[-0.636,-0.157]
Computer X Age					**0.075***
					[-0.012,0.169]
Observations	108	108	108	108	108

Notes: The table shows regression results from the estimation of equation 2. Confidence intervals are estimated using the wild cluster bootstrap method, and clustering is performed at synthetic panel groups. Controls include occupational fraction of individuals whose political spectrum is reported liberal, occupational job posting share, occupational employment share. Fixed effects include age, year, and interaction of age and year in the synthetic panel. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Giuliano and Spilimbergo (2014)).

In column five I include computer task, occupation-specific average worker ages, and their interaction. After controlling for the average worker age, the point estimates of computerization are even larger, -3.912, and statistically significant. An increase in the average age has a negative impact, which may reflect higher work experiences contributing to higher labor income. The interaction term is shown positive, on the other hand, which may indicate that older workers faced with an increase in computer task are more supportive toward redistribution preferences. This may be due to skill obsolescence: meaning that older workers whose skills are relatively far from frontiers of new technologies in the labor market experience significant earnings loss as studied in Braxton and Taska (2019).

2.4.4 Pre-existing trends and anticipation effects

The key threat to the validity of the interpretation that technological change is leading to reductions in people's desires for government redistribution is some violation of the parallel trends assumption. That is, absent the treatment from technological change, redistribution preferences in different occupations would have grown, in expectation, at the same rate.

There are several plausible scenarios that could violate this assumption. One scenario relates to structural transformation and occupational divergence. In other words, highly computerized occupations were already experiencing lower desires for redistribution relative to slowly computerized occupations because of, say, broader structural change (e.g., shift away from agricultural goods-producing activities toward commodity goods-producing activities). As discussed already, occupations facing faster computerization are higher paying occupations, and they are typically expanding occupations.

A second scenario relates to unobserved shocks that spuriously correlate with the change in computerization exposure. An example would be a change in the political spectrum leaning toward conservatism. In this example, because conservatism correlates with composition of workers in occupations, the results may reflect the unobserved shift in political attitude and not the effect of computerization. Regarding the discussion about changes in redistribution preferences above, this is an important concern.

To explore these issues, my strategy is to project redistribution preferences on interactions between time and computer task intensity as of the final available observation. The interactions between time and computer task intensity is designed to check for any pre-existing trends. Moreover, these are the same set of interactions explored in the baseline specification. The event study specification is:

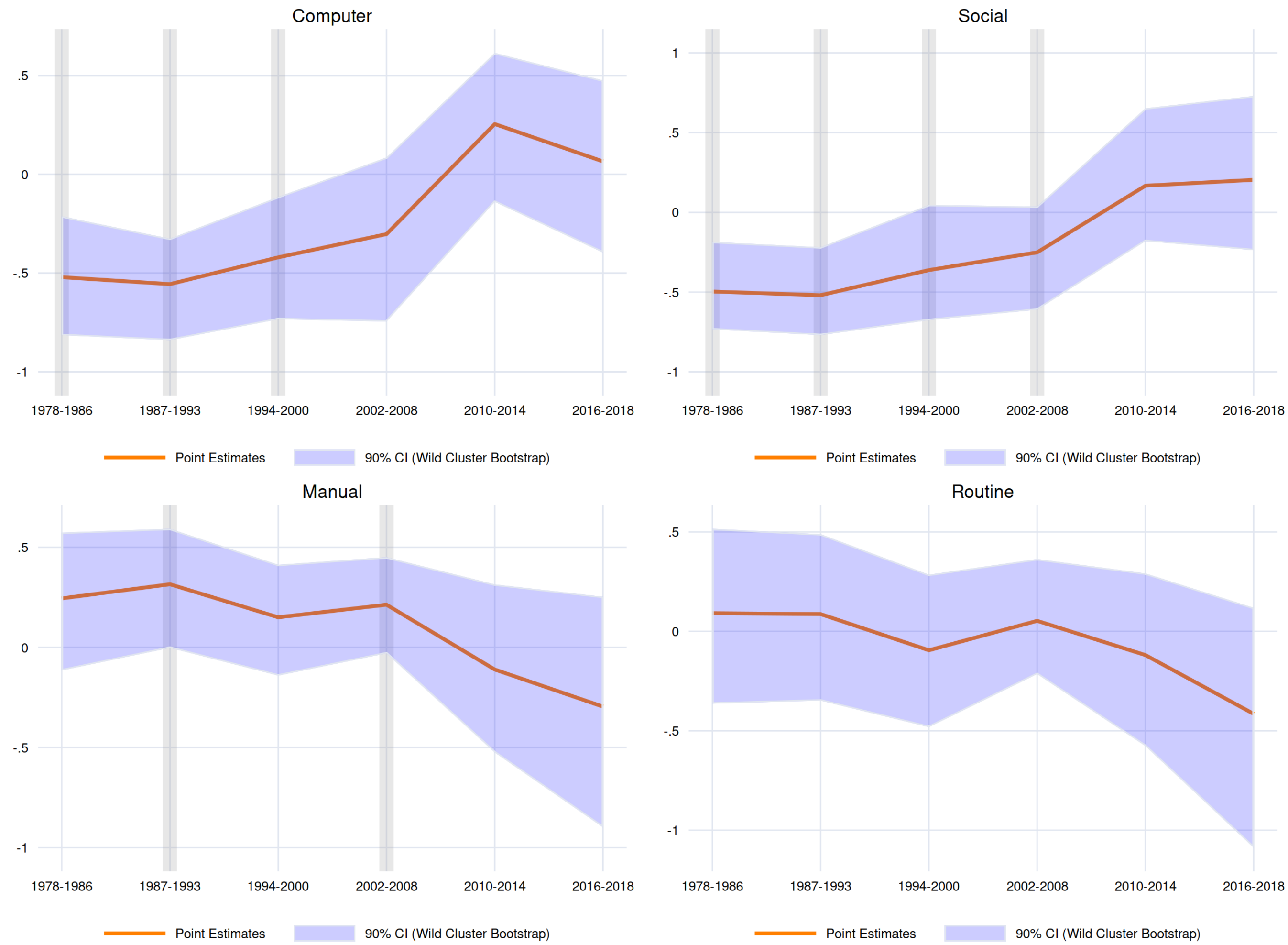
$$\text{Redist}_{aot} = \sum_{t=\text{initial period}}^{\text{end period}} \text{Task Intensity}_{o,\text{end period}} \beta_t + \alpha + \eta_t X_o^{'} \delta + X_{ot}^{'} \lambda + \gamma_a + \eta_t + \gamma_a \times \eta_t + \epsilon_{aot}$$

where the sum on the right-hand side interacts a time dummy with the task intensity as of the end-period of the sample. To focus solely on reaction of preferences to task intensity holding changes in income fixed, occupational earnings in every period are controlled. As before, confidence intervals are estimated using the wild cluster bootstrap method and clustering is performed at synthetic cohort groups.

Figure 2 plots the results for each type of tasks. For each task type, the coefficients β_t and 90-10 confidence intervals associated with them are plotted. Periods when the estimates of β_t are statistically different from zero are shaded. This means that for unshaded periods, the computer task intensity as of the end period is uncorrelated with redistribution preferences. As it is seen in the coefficient plots, there are no noticeable trends for the four decades. That is, the results from the event study are supportive of the parallel trends assumption.

The β_t coefficient becomes statistically different from zero prior to the end period. The sign when the coefficients are significant is negative, which is qualitatively consistent with the empirical results in Table 1. That the coefficients prior to the end-period task intensity are significant and statistically different from zero suggests that forward-looking workers are anticipating the future status of technological progress. Consequently, workers have lower desires for government redistribution.

Figure 2: Event Study Regression: Synthetic cohorts



Notes: Panels display the effects of end-period task intensity on preferences for government redistribution against income inequality measured as standardized coefficients. Shaded periods denote when the technological change effect of the end period is statistically significant at 10%. Confidence intervals are estimated using the wild cluster bootstrap method, and clustering is performed at synthetic panel groups. Controls include occupational fraction of individuals whose political spectrum is reported liberal, occupational job posting share, occupational employment share. Fixed effects include age, year, and interaction of age and year in the synthetic panel.

Overall, combined with the fact that there are no detectable trends with respect to the end-period of task intensity, and redistribution preferences react to the future task intensity, they are supportive of the results in the baseline specification. This also supports evidence at a different angle that computerization causes changes in redistribution preferences.

2.4.5 Discussion

This section summarizes and discusses the key empirical results to facilitate exposition in what follows: macroeconomic implications of the empirical evidence.

Figure 1 (result at the 3-digit level in Figure A1) clearly shows that the increase in computer task intensity has been concentrated in higher-paying occupations. Given this result, a natural question is whether computerization has a distinct effect from occupational earnings on redistribution preferences. I provide an explanation for why desires for government redistribution may decrease when occupations are exposed computerization, and why this technological change effect is distinct from impacts from occupational earnings.

For simplicity, suppose that skill composition of individuals is fixed during computerization. The positive slope for computer task intensity in Figure 1 may suggest a decrease in redistribution preferences of individuals *only* in higher-paying occupations through gains in occupational earnings, and an increase for those in lower-paying occupations. In this case, the impact of technological change would be absorbed by net gains in occupational earnings, if occupational earnings are controlled for.

However, if their skill composition is fungible during computerization, this technological change would generate an incentive to invest in skill accumulation, and these effects would not be captured solely by the earnings effects. Moreover, given that government redistribution decreases this skill investment incentive, technological change would reduce desires for redistribution of a wide range of individuals. As a result, the effect can be substantial while controlling for earnings, which is seen in column two in Table 1.

While the increase in social task intensity has similar pattern, column three in Table 1, when both computer and social tasks are included together, shows that effects of social task are not significant, and they are mainly due to computerization.

Regarding routine and manual tasks, magnitudes of point estimates in column four and five in Table 1 are smaller and they are not statistically different from zero. That is, their effects are relatively miniscule even when earnings are not controlled for.

In sum, empirical results in Section 2 show that individual preferences for redistribution decrease in response to technological change. These effects are viable even with occupational earnings, and potentially due to the skill investment channel. In what follows, in Section

3, I formalize this intuition using a simple model of an individual skill investment choice. I develop a quantitative model in Section 4 and see whether the proposed mechanism can rationalize the aggregate trends in income inequality and government redistribution. Quantitative results are reported in Section 6.

3 Simple Model of Skill Investment and Redistribution

To build the intuition of the empirical results in Section 2, here I present a simple model of skill investment and government redistribution that illustrates the key trade-off of workers' demand for redistribution during technological change. In particular, the model of this section ties the decline in the demand for redistribution to workers' skill investment and computerization I consider in the fully-fledged model of Section 4, the key reason for the reduction in desires for tax progressivity when prices of equipment goods decrease.

Consider an economy populated by a continuum of workers who work in occupation groups $o = 1, \cdots, O$ with employment shares π_o summing to one, and invest their time x in acquiring skills, which increases their pre-tax earnings. Workers are faced with utility costs of skill investment φ_o different by occupations. The government runs a fiscal policy of two parameters (λ, τ), where λ governs the average level of workers' post-tax earnings and τ is tax progressivity, as in Heathcote et al. (2017). A worker solves

$$V\left(\lambda, \tau, q, \{\varphi_o\}_o, \kappa\right) = \max_{c,x}\left\{\log c - \varphi_o \frac{x^{1+\frac{1}{\kappa}}}{1+\frac{1}{\kappa}} \quad s.t. \quad c = (1-\lambda)\left[x^q\right]^{1-\tau}\right\}$$

where κ is the elasticity of costly skill investment, and q is the efficiency of computer equipment. A worker's pre-tax earnings are x^q and after-tax earnings are $(1-\lambda)\left[x^q\right]^{1-\tau}$, which are increasing in q. In the quantitative model in Section 4, the efficiency of different types of equipment goods are considered, reflecting capital-embodied technological change in general.

It is straightforward to show that the solution of the worker's problem implies desires for tax progressivity as a function of skill investment costs φ_o and the efficiency of computers q. For workers in an occupation with sufficiently lower skill investment costs than other occupations, their desires for tax progressivity is relatively lower than workers in other occupations. The first result in Proposition 1 constructs it formally. Moreover, this gap is widened when computerization progresses and the skill investment is elastic. The second result in Proposition 1 shows this, on top of the first result.

Proposition 1. *Let $\varphi_{o'} - \varphi_o > 1$ for o, o' with $o \neq o'$, $\tau < \tau'$, and utility gains of workers in occupation o from lower tax progressivity $\Delta_\tau V_o \equiv V_{o,\tau} - V_{o,\tau'}$. Then utility gains of workers in occupation o is higher than utility gains of workers in occupation o', i.e.,*

$$\Delta_\tau V_o - \Delta_\tau V_{o'} > 0.$$

Moreover, an increase in the efficiency of computer equipment q or the higher elasticity of skill investment κ increases the utility differential $\Delta_\tau V_o - \Delta_\tau V_{o'}$.

Proof. See Appendix B.1. □

The first result establishes that gains from lower tax progressivity are greater if costs of acquiring skills in an occupation are substantially lower than other occupations. This relationship would not hold if there is no substantial heterogeneity in skill investment costs across occupations in general.

The second result in Proposition 1 uses the first result to show that computerization and elastic skill investment together play a key role in widening the gap in redistribution gains. Intuitively, workers whose skill investment costs are relatively low get benefits from technological change favoring skill acquirement. Also, these benefits are higher if the elasticity of skill investment is higher.

This simple example indicates that the ability of the model to account for the decline in the desires for tax progressivity depends crucially on the trade-off between skill investment and redistribution – the equity-efficiency trade-off – and heterogeneous returns to skill investment by occupations.

In principle, an increase in the efficiency of computer equipment would have an ambiguous effect on the aggregate demand for redistribution, because greater tax revenue also implies greater transfer. For low-income workers, it is intuitive to predict that these equity concerns outweigh the efficiency concerns.

However, this simple model abstracts from several important elements that shape gains from redistribution (e.g., general equilibrium of fiscal policy, workers' occupatoinal choices, elastic labor supply, productivity risk). Moreover, the ultimate redistribution also relies on the fact that voter groups politically compete by voting for their desired policy in reality. The next section considers these elements in a fully-fledged quantitative model.

4 Quantitative Model

Based on the empirical findings, I develop a tractable quantitative general equilibrium political economic model in which workers consider costly college education choices before entering the labor market, select occupations based on comparative advantage, and vote for redistribution policy modeled as the progressive tax system. The developed model departs from the existing literature in several aspects. The economic block of the model is a synthesis of the task-based approach (e.g., Autor et al. (2003), Acemoglu and Autor (2011), Autor and Dorn (2013)) and the multi-sector assignment framework following the Roy (1951) tradition (e.g., Heckman and Sedlacek (1985), Atalay et al. (2018), Burstein et al. (2019)), extended with risk-averse preferences, work-leisure trade-off, and fiscal institution modeled as non-linear tax-and-transfer system. The political block of the model is an estimable version of the probabilistic voting theory as in Stromberg (2008), which is a workhorse model of political economy. The key difference from his work is integration of the estimable political theory in a standard general equilibrium environment, where policy preferences are explicitly micro-founded by deriving indirect utilities up to government policies based on primitives. Third, I relax the assumption of fixed worker/voter groups by allowing for agents to decide their identity through college education choice before entering the labor market.[14]

For brevity, I put aside details of the computation algorithm to Appendix C. The algorithm is in close connection to the nested fixed-point nature of political general equilibrium, explicated as in Krusell and Rios-Rull (1999).

4.1 Environment

Demographics, worker productivity Each worker i belongs to one of demographic groups indexed by $g = 1, \cdots, G$ and distinguished by age, gender, and education, i.e. $G \equiv \{\text{Age}\} \times \{\text{Gender}\} \times \{\text{Education}\}$. I consider three age groups (young, middle, old) and two education levels (high school diploma, college graduates). Each group has a measure N_g, a relative population share $\pi_g \equiv N_g / \sum_g N_g$. A worker i in group g is endowed with labor productivity H_g, which is common within the same demographic group across workers.

Before entering the labor market, workers in the young age group consider costly college education choices $d \in \{\text{HS,Coll}\}$. If that worker i chooses to be a college graduate, he incurs utility costs $\chi_{d,g=y}$ relative to when he decides to remain at the high school diploma

[14] For example, analyses with exogenous demographic composition are limited by not allowing for agents to respond to an anticipated change in the economic environment (e.g., Atalay et al. (2018); Hsieh et al. (2019); Burstein et al. (2019)). Similarly, the canonical probabilistic voting models (e.g., Lindbeck and Weibull (1987); Dixit and Londregan (1996)) assume fixed voter groups.

level, which is unmodeled composite costs of pursuing higher education (e.g. tuition fees, gender discrimination), as in Hsieh et al. (2019). These career costs $\chi_{d,g=y}$ are assumed to be different by gender in order to capture differing college graduate share by gender observed in data. In addition, that worker i is subject to identically and independently drawn (i.i.d.) preference shocks $\zeta_{id,g=y}$ that follow the standard bivariate Gumbel distribution.

Once a worker i enters the labor market, he has two roles. First, each worker i as an economic agent maximizes utility by purchasing consumption goods c, choosing work hours h out of the unit endowment of time, and selecting occupation-equipment pair (o, e) to work. Each pair is jointly defined by occupation $o = 1, \cdots, O$ (e.g., engineer, bookkeeper, construction worker), equipment $e = 1, \cdots, E$ (e.g. electric drills, portable computers, Point of Sales at grocery store).[15] Within occupation, a worker accumulates skills depending on how many hours to work h and occupation-specific returns to time investment ϕ_o. Hence, productivity of a worker from demogrpahic group g who work in occupation o is $H_g \times h^{\phi_o}$. A worker also draws i.i.d. idiosyncratic productivity over all possible pairs of occupation and equipment $\epsilon = (\epsilon_{ioe})_{oe}$ that follow the multivariate Frechet distribution $F_\epsilon(\epsilon)$ with the shape parameter θ, which governs within-worker dispersion of productivity. Second, that worker i as a voter chooses an electoral candidate from party $x \in \{L, R\}$ to support.

Preferences of workers Following the canonical probabilistic voting theory, preferences of each worker i consist of two components: economic and political preferences. Economic preferences of each worker i are defined over objects of economic interest (e.g. consumption, leisure), which constitutes preferences for economic policy (i.e., policy preferences). Political preferences of each worker i are derived preferences over non-economic interest (e.g. same-sex marriage, abortion), which gauge non-economic utility benefits from the fixed position of political party $x \in \{L, R\}$. The political preferences consist of three additive parts $R_{igt} + \eta_{ig} + \eta_i$, where R_{igt} is the group-specific and predictable when electoral candidates choose policy packages in elections, and η_{ig}, η_i are group-specific and aggregate swings that are known to the candidates once they propose an economic policy package. I assume that these components are drawn from the normal distributions, $R_{igt} \sim F_R = \mathcal{N}\left(\mu_{gt}, \sigma_{gt}^2\right)$, $\eta_{ig} \sim \mathcal{N}\left(0, \sigma_g^2\right)$, $\eta_i \sim \mathcal{N}\left(0, \sigma^2\right)$, where mean and variance parameters of the distribution of predictable preferences can vary over time. The utility function of a worker i is

[15] The way in which production units are defined is to capture that in the skill content data occupations exhibit substantial heterogeneity in the extent to which different types of equipment are used, and demographic composition in occupational employment distribution.

$$U_i = \underbrace{\log c_i - \varphi \frac{h_i^{1+\frac{1}{\xi}}}{1+\frac{1}{\xi}} - \chi_{d,g=y} + \zeta_{id,g=y}}_{\text{economic}} + \underbrace{R_{igt} + \eta_{ig} + \eta_i}_{\text{political}}$$

where in the economic preferences the first two terms c_i, h_i are preferences for consumption and leisure, φ is disutility of work, and ξ is the labor supply elasticity. The next two terms $\chi_d, \zeta_{id,g}$ are costs and preferences shocks to education choices. In the political preferences, the first term R_{igt} is predictable and the next two η_{ig}, η_i are non-predictable.

It is assumed that $\psi_g \in (0,1)$ fraction of voters in group g participates in elections, which captures that in data turnout rates are different substantially across demographic groups and far from the unity. Turnout rates ψ_g are endogenous to the extent that young voters decide costly education choice d, and are constant once they enter the labor market.

Fiscal institution The fiscal institution runs the non-linear tax schedule on labor income, parametrized as in Bénabou (2002) and Heathcote et al. (2017)

$$\mathcal{T}\left(y_i; \lambda_x, \tau_x\right) = y_i - \left(1 - \lambda_x\right) y_i^{1-\tau_x}$$

where λ_x governs average levels of post-tax earnings, τ_x determines progressivity of the income tax schedule, y_i is pre-tax income of an individual i, and $\left(1-\lambda_x\right) y_i^{1-\tau_x}$ is post-tax income. Each electoral candidate $x \in \{L, R\}$ can propose a different tax schedule. Tax revenues are used to finance (wasteful) government expenditures G, which is exogenous, and taken as given by both candidates. The balanced budget constraint leads to the requirement that government expenditures must be equal to tax revenues

$$G = \sum_{o,e,g} \int_{i \in \Omega_{oeg}} N_g \mathcal{T}\left(y_i; \lambda_x, \tau_x\right) dF_\epsilon\left(\epsilon\right)$$

where $\Omega_{oeg} \equiv \{i | U_{ioe} \geq U_{io'e'},\ \forall\left(o,e\right) \neq \left(o',e'\right)\}$ is the set of workers from demographic group g who select an occupation-equipment pair (o,e). This fiscal structure is taken as given by electoral candidates.

Preferences of politicians, political institution Office-motivated electoral candidates are nominated from parties $x \in \{L, R\}$, whose preferences are given by binary preferences

$$U_x = \begin{cases} 1 & \text{if } x \text{ wins} \\ 0 & \text{otherwise} \end{cases}$$

That is, electoral candidates receive strictly positive felicity if they win an electoral competition. Each candidate maximizes her utility by proposing a policy (λ_x, τ_x) that shapes the tax schedule described in the fiscal institution, subject to the constraints: (1) the government budget constraint is satisfied and (2) all markets are cleared. I assume electoral candidates maximize the expected vote share subject to the constraints above.[16]

Production technology The final goods Y is used for consumption and producing equipment goods, and is the standard constant-elasticity-of-substitution (CES) aggregator of occupational goods Y_o

$$Y = \left(\sum_o Y_o^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}}$$

where $\rho > 0$ the elasticity of substitution across occupational goods Y_o. I set the final goods as a numeraire. Each occupational goods Y_o is the sum of all outputs from production units pertaining to that occupation o. Each production unit produces Y_{oeg} by hiring units of e-type equipment and efficiency hour units of a worker of g-type demographic group

$$Y_{oeg} = \prod_s (T_{oegs})^{\alpha_{oes}} k_e^{1-\sum_s \alpha_{oes}}, \quad T_{oegs} = H_g \times h^{\phi_o} \times l_{oegs},$$

where $s = 1, \cdots, S$ is an index for different types of task (e.g. computer, social, manual, and routine), α_{oes} represents relative importance of task s when paired with equipment e within occupation o, such that income share of labor is $\sum_s \alpha_{oes} < 1$ for each (o, e) pair, and $1 - \sum_s \alpha_{oes}$ is the income share of equipment. Inputs of production are task output T_{oegs}, which is produced by combining the unit of time spent producing s-type task l_{oegs} and labor productivity $H_g \times h^{\phi_o}$, and units of e-type equipment k_e. Once a worker from group g is hired, a firm distributes the worker's hours h into task types l_{oegs} unit of time to produce $H_g \times h^{\phi_o} \times l_{oegs}$ where tasks are indexed by by $s = 1, \cdots, S$.

The e-type equipment goods is produced by a linear technology $k_e = q_e Y_e$ which transforms Y_e units of final goods into the k_e units of equipment goods. That is, q_e is the transformation rate that governs how efficiently the equipment goods is produced relative to consumption goods.[17]

[16] This is the standard assumption in the canonical probabilistic voting theory (e.g., Dixit and Londregan (1996); Persson and Tabellini (2002)). This simplification in an applied setting is mainly due to the infinite-dimensional nature of the probabilistic voting theory. For details, see discussions in Lindbeck and Weibull (1987) and Stromberg (2008).

[17] This captures the notion that the technological progress enhances the efficiency of producing the equipment goods, and therefore, lowers prices of equipment goods (e.g. Greenwood et al. (1997), and Caunedo et al. (2021)).

Timing of events Timing of events is as follows. First, the political event is held. In an election, individuals draw political preferences $R_{ig}, \eta_{ig}, \eta_i$, politicians forecast predictable preferences R_{ig} and propose a policy package, and voters choose a candidate from the parties $x \in \{L, R\}$ to cast their votes. A winner is determined under the majority rule and takes the fiscal institution and implements a proposed policy.

Given that a policy has been implemented, young workers draw and observe shocks $\zeta_{id,g=y}$ and career costs $\chi_{d,g=y}$ and skill levels H_g across demographic groups. Anticipating prices for efficiency hour units of labor P_{oeg}, they decide whether or not to receive college education, and enter the labor market.

Given that a policy has been implemented and young workers have made the education choice, workers enter the labor market, and draw and observe ϵ_{ioe} for all possible occupation-equipment pairs. Given the realization of ϵ_{ioe}, the young worker selects a pair and chooses work hours to maximize utility.

This sequence of events implies that an analysis is backward. That is, in the last and second-to-last events workers formulate indirect utility up to government policy, and in the first event workers are given political preferences, and electoral candidates look forward and propose a policy to maximize the expected vote share.

4.2 Workers

In the last stage, a worker i chooses work hours h_i and consumption c_i by selecting into an occupation-equipment pair (o, e). Given policy proposals (λ_x, τ_x), each worker i from demographic group g maximizes utility

$$
\begin{aligned}
V_{ioeg}(\lambda_x, \tau_x) \equiv & \max_{c_i, h_i} \log c_i - \varphi \frac{h_i^{1+\frac{1}{\xi}}}{1+\frac{1}{\xi}} \\
s.t. \quad c_i = & P_{oeg} h_i \epsilon_{ioe} - \mathcal{T}(P_{oeg} h_i \epsilon_{ioe}; \lambda_x, \tau_x) = (1-\lambda_x)(P_{oeg} h_i \epsilon_{ioe})^{1-\tau_x}
\end{aligned}
$$

In the second stage, a worker i in the young age group solves the problem of whether or not to receive college education before his idiosyncratic productivity ϵ_{ioe} is realized. The college education choice of a young worker is

$$
\begin{aligned}
\pi_{g=y}(\lambda_x, \tau_x) = & \arg\max_{d \in \{\text{Coll,HS}\}} \{V_{d,g=y}(\lambda_x, \tau_x) - \chi_{d,g=y} + \zeta_{id,g=y}\} \\
& s.t. \quad V_{d,g=y}(\lambda_x, \tau_x) = \mathbb{E}_\epsilon \left[\max_{(o,e)} \{V_{ioe,g=y}(\lambda_x, \tau_x)\} \right]
\end{aligned}
$$

where $V_{d,g=y}(\lambda_x, \tau_x)$ is the expected utility from earnings the young receive in the labor market. In other words, a young worker compares the expected returns to college education, which depends on market earnings and redistributive tax policy (λ_x, τ_x). In its essence, the trade-off with which a young worker is faced depends on the likelihood that their most preferred policy is realized in equilibrium. By the law of large number, shares of college-educated young workers is consistent with the individual choice probability.

4.3 Firms

Given prices of occupational goods P_o and the final goods technology, the final good producer chooses how much occupational goods to use Y_o to maximize profits

$$\max_{\{Y_o\}_o} \left(\sum_o Y_o^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}} - \sum_o P_o Y_o$$

Given prices per efficiency hour units of a worker from group g who chooses (o, e) pair P_{oeg} prices of equipment goods P_e and prices of occupational goods P_o, firms that operate production units choose how many units of equipment type-e to use k_e and efficiency hour units of a worker from demographic group g to hire n_g that are distributed across tasks. The production unit firms maximize profits

$$\max_{k_e, n_g, \{l_{oegs}\}_s} P_o \prod_s (T_{oegs})^{\alpha_{oes}} k_e^{1-\sum_s \alpha_{oes}} - P_{oeg} n_g - P_e k_e, \quad T_{oegs} = H_g \times h^{\phi_o} \times l_{oegs}$$

Given prices of equipment P_e and the transformation rate q_e, the equipment goods producer chooses how much units of final goods to use Y_e. They maximize profits

$$\max_{Y_e} P_e q_e Y_e - Y_e$$

4.4 Characterization - partial equilibrium

To ease exposition, I characterize partial equilibrium conditional on prices of occupational goods P_o and policy proposals (λ_x, τ_x), before defining a competitive equilibrium up to exogenous policy, and political general equilibrium. For details of all derivations in this section see Appendix B.4.

Prices per efficiency hour units of labor P_{oeg} are derived from the profit-maximizing production unit firm's optimal equipment unit demand and zero-profit condition

$$P_{oeg}\left(\tau_x\right) = \underbrace{\bar{\alpha}_e\left(1-\bar{\alpha}_e\right)^{\frac{1-\bar{\alpha}_e}{\bar{\alpha}_e}}}_{\text{factor shares}} \times \underbrace{P_o^{\frac{1}{\bar{\alpha}_e}}}_{\text{GE eff.}} \times \underbrace{q_e^{\frac{1-\bar{\alpha}_e}{\bar{\alpha}_e}}}_{\text{equip. eff.}} \times \underbrace{\left\{\prod_s \left(H_g \frac{\alpha_{oes}}{\bar{\alpha}_e}\left(\frac{1-\tau_x}{\varphi}\right)^{\frac{\xi(1+\phi_o)}{\xi+1}}\right)^{\frac{\alpha_{oes}}{\bar{\alpha}_e}}\right\}}_{\text{task-labor productivity}} \tag{3}$$

where $\bar{\alpha}_e = \sum_s \alpha_{oes}$ is the share of labor income. The equation above indicates that prices per efficiency hour units of labor consist of (1) income share, (2) general equilibrium effects through occupational goods markets, (3) equipment efficiency, (4) composite task-labor productivity. The last term is comprised of group-specific labor productivity, task importance, leisure-work trade-off, on-the-job skill accumulation, the elasticity of work hours, and tax progressivity. In sum, the payment to work reflects a worker's comparative advantage.

This comparative advantage governs the pattern of selection over (o, e) pairs, in addition to idiosyncratic productivity. As a result, a worker's selection problem is the standard random utility framework (McFadden (1973)). Define a choice probability that a worker from group g chooses (o, e) pair as

$$\pi_{oeg}\left(\lambda_x, \tau_x\right) = \Pr\left\{\log\left(1-\lambda_x\right)\left(P_{oeg} h_i \epsilon_{ioe}\right)^{1-\tau_x} - \varphi \frac{h_i^{1+\frac{1}{\xi}}}{1+\frac{1}{\xi}}\right.$$
$$\left. > \max_{(o,e)\neq(o',e')} \log\left(1-\lambda_x\right)\left(P_{o'e'g} h_i \epsilon_{ioe}\right)^{1-\tau_x} - \varphi \frac{h_i^{1+\frac{1}{\xi}}}{1+\frac{1}{\xi}}\right\}$$

Under the Frechet distribution, an analytical expression of the choice probability is obtained. The resulting choice probability is a function of scaled payment to efficiency hour units, which reflects workers' comparative advantage

$$\pi_{oeg}\left(\tau_x\right) = \frac{P_{oeg}\left(\tau_x\right)^{\theta}}{\sum_{o',e'} P_{o'e'g}\left(\tau_x\right)^{\theta}} \tag{4}$$

It is worth noting several points. First, the choice probability is a fraction of price per efficiency hours units scaled by the parameter governing within-worker dispersion of idiosyncratic productivity ϵ_{ioe}. Second, the occupation-equipment selection depends solely on comparative advantage in partial equilibrium, while in general equilibrium, there are redistribution gains through the government budget where the average tax level λ_x governs levels of post-tax earnings, and price effects through occupational market clearing.

To see the channel of redistribution gains, note that the expected earnings of a worker in demographic group g selecting (o,e) pair is

$$w_g(\lambda_x,\tau_x) = (1-\lambda_x)\, h(\tau_x)^{1-\tau_x}\, \Gamma\left(1-\frac{1-\tau_x}{\theta}\right)\left\{\sum_{o',e'} P_{o'e'g}(\tau_x)^{\theta}\right\}^{\frac{1-\tau_x}{\theta}} \tag{5}$$

where λ_x scales levels of post-tax income proportionally. Through the trade-off between linear and non-linear tax features of tax system (λ_x,τ_x), and because the progressive tax collects revenues more from higher earners who have higher comparative advantage and/or better luck to random productivity, workers from different demographic backgrounds cannot be aligned in their most preferred policy.

Provided that an equilibrium policy is pinned down by electoral competition, understanding how preferences for policy (λ_x,τ_x), is shaped has the first-order importance. To this end, define maximal values per each (o,e) pair as $V_{ioeg}(\lambda_x,\tau_x)$

$$\begin{aligned} V_{ioeg}(\lambda_x,\tau_x) \equiv \Bigg\{ & \log(1-\lambda_x)\left(P_{oeg}h_i\epsilon_{ioe}\right)^{1-\tau_x} - \varphi\frac{h_i^{1+\frac{1}{\xi}}}{1+\frac{1}{\xi}} \\ & > \max_{(o,e)\neq(o',e')} \log(1-\lambda_x)\left(P_{o'e'g}h_i\epsilon_{io'e'}\right)^{1-\tau_x} - \varphi\frac{h_i^{1+\frac{1}{\xi}}}{1+\frac{1}{\xi}} \Bigg\} \end{aligned}$$

In an electoral stage, politicians are concerned about voters' expected indirect utilities up to their policy proposal (λ_x,τ_x). Since (λ_x,τ_x) are aggregate variables to be determined in political equilibrium, it is useful to define a competitive equilibrium for a given policy proposal (λ_x,τ_x).

4.5 Competitive equilibrium up to exogenous policy

In any period, prices of occupational goods P_o must clear the occupational goods market conditional policy proposals (λ_x,τ_x) for all $x\in\{L,R\}$. Occupational market clearing states that for each occupation

$$Y(\lambda_x,\tau_x)\, P_o^{-\rho}(\lambda_x,\tau_x) = \sum_{e,g}\int_{i\in\Omega_{oeg}} N_g(\lambda_x,\tau_x)\, h_i(\tau_x)\,\epsilon_{ioe} Y_{oeg}(\tau_x)\, dF_\epsilon(\epsilon)$$

where Ω_{oeg} is the set of workers i from demographic group g who select (o, e) pair. The left-hand side is demand for occupational goods by the final goods producer and the right-hand side is supply of occupational goods. The Walras law implies that final goods market clears

$$\sum_{e} Y_e(\lambda_x, \tau_x) + \sum_{g} \int_{i \in \Omega_{oeg}} N_g(\lambda_x, \tau_x)\, c_i(\lambda_x, \tau_x)\, di + G = Y(\lambda_x, \tau_x)$$

where G is given from the budget constraint of the fiscal institution, which is reproduced below to make clear the dependence on policy proposals (λ_x, τ_x)

$$G = \sum_{o,e,g} \int_{i \in \Omega_{oeg}} N_g \left[P_{oeg}(\tau_x)\, h_i(\tau_x)\, \epsilon_{ioe} - (1 - \lambda_x) \left[P_{oeg}(\tau_x)\, h_i(\tau_x)\, \epsilon_{ioe} \right]^{1-\tau_x} \right] dF_\epsilon(\epsilon)$$

This completely characterizes the economic block up to (λ_x, τ_x), which is pinned down by the political block. It is the notion of standard competitive equilibrium given a set of exogenous policies. Next, I introduce the political process that pins down an equilibrium policy and closes the model.

4.6 Political general equilibrium

The political block, electoral competition, closes the model by pinning down a policy, which is consistent with the economic block. Proposition 2 characterizes the electoral equilibrium.

The political block is a standard probabilistic voting theory extended in which I relax the standard assumption of fixed voter groups through the education decision. Voter groups vary depending on economic primitives, and the likelihood of their most preferred policy.

Proposition 2 **(Political process).** *Given the political weight ω_g, electoral candidates $x \in \{L, R\}$, subject to that the government budget constraint is satisfied, all markets clear, propose policies that maximize the expected vote share:*

$$(\lambda^*, \tau^*) = (\lambda_L, \tau_L) = (\lambda_R, \tau_R) = \arg\max_{(\lambda_x, \tau_x)} \sum_{g} \omega_g \times \psi_g \times \pi_g(\lambda_x, \tau_x) \times V_g(\lambda_x, \tau_x)$$

where the political weight ω_g arises as:

$$\omega_g = \phi\left(-\sigma_{gt}^{-1}\left(\mu_{gt} + \eta_{ig} + \eta_i\right)\right)$$

where $\phi(\cdot)$ is the probability density function of the standard normal distribution. $V_g(\lambda_x, \tau_x)$ is the expected indirect utilities up to policy proposal, i.e., $V_g(\lambda_x, \tau_x) = \mathbb{E}_\epsilon\left[V_{ioeg}(\lambda_x, \tau_x)\right]$.

Proof. See the Appendix B.2. □

The definition of political general equilibrium is standard, and a concise description of the aforementioned characterization.[18]

In an electoral stage, political candidates maximize the symmetric expected vote share. This expected vote share is a weighted average of expected indirect utilities up to policy proposal (λ_x, τ_x). Unlike the social planning problem, however, the weights arise as outcomes in equilibrium, which is consistent with behavioral rules of politicians.

Because the expected indirect utilities are integrated maximal values over all possible pairs of idiosyncratic productivity, solving for political general equilibrium is to evaluate these high-dimensional objects, each of which depends on the entire voter distribution.

The theory of extreme values states that a maximum of extreme values is also extreme-value distributed. Given the distributional assumption, this property not just simplifies the problem considerably, but also articulates why a voter may want more or less redistribution. Proposition 3 provides a closed-form expression of the indirect utilities up to (λ_x, τ_x).

4.7 Dissecting demand for redistribution

This section provides an analytically tractable expression for a worker's expected indirect utilities up to policy proposal (λ_x, τ_x). This is an otherwise high-dimensional object that must be evaluated numerically. To this, tractability provides a closed-form expression, which greatly reduces the computational burden.

Proposition 3 (Demand for redistribution). *Assume $\theta > 1$, and $\lambda_x, \tau_x \neq 1$ for all $x \in \{L, R\}$. The expected indirect utilities of a worker from demographic group g up to policy proposal (λ_x, τ_x) exist and satisfy the following equation:*

$$V_g(\lambda_x, \tau_x) \equiv \mathbb{E}_\epsilon \left[V_{ioeg}(\lambda_x, \tau_x)\right] = \underbrace{\log \sum_{o,e} P_{oeg}(\tau_x)^{1-\tau_x}}_{\textit{compress comparative advantage}} + \underbrace{\frac{\gamma_{em}}{\theta}(1-\tau_x)}_{\textit{compress idiosyncratic risk}} + \underbrace{\log(1-\lambda_x)}_{\textit{redistribution gains}}$$
$$+ \underbrace{\log\left(\frac{1-\tau_x}{\varphi}\right)^{\frac{\xi(1-\tau_x)}{1+\xi}}}_{\textit{counteracting effects on hours}} - \underbrace{(1-\tau_x)\frac{\xi}{1+\xi}}_{\textit{gains from less hours}}$$

where $\gamma_{em} = 0.57721...$ is the Euler-Mascheroni constant and θ is the shape parameter of the multivariate Frechet distribution.

Proof. See the Appendix B.3. □

[18] This equilibrium notion is in line with the notion as described in Persson and Tabellini (2002), and Krusell and Rios-Rull (1999) in the sense that an economic policy arises as the equilibrium outcome of a well-defined non-cooperative game under primitive assumptions about economic and political behavior.

Tractability also enables unpacking a worker's demand for redistribution with a transparent manner. Proposition 3 describes underlying motives why worker/voter groups may have different desires for government redistribution.

The first term, the (log) sum of tax-compressed price per efficiency hour units, implies the redistribution role for comparative advantage ("hard work"). Given that the pre-tax price per efficiency hour units is payment to the worker's composite productivity, a progressive tax compresses the worker's productivity. In Section 6, I demonstrate that this efficiency concern is the key mechanism in explaining why technological change may lead to the reduction in individual redistribution preferences and tax progressivity at the aggregate level.

The second term, dispersion-adjusted tax progressivity, implies the redistribution role for productivity draws. While progressive tax reduces overall levels of indirect utilities, this welfare loss is decreasing in dispersion parameter θ, in which as the higher θ is the expected earnings also increases (see equation 5).

The third term is the redistribution gains or losses from a progressive tax. These redistribution gains are comprised of two components. On the one hand, it is consequences from the redistribution role for comparative advantage ("hard work"). Consider two workers who draw the same idiosyncratic productivity, but possess different composite productivity. Due to a progressive tax, a worker with higher productivity likely incurs redistribution losses, i.e., he has to pay more than what he receives.

On the other hand, there is the insurance role for productivity risk ("luck"). Suppose, for example, a worker who draws substantially lower idiosyncratic productivity. This worker is likely better off by redistribution relative to other workers drawing sufficiently high "luck". Since workers are risk-averse, the greater ex-ante productivity dispersion is, the more gains from the insurance role of the tax progressivity are.

The fourth and fifth terms are counteracting effects on hours worked. On the one hand, higher progressivity decreases an incentive to work longer by pulling down payment to worker's comparative advantage. On the other hand, fewer hours increase the worker's utility by increasing their leisure time. In sum, the relationship between progressivity and work hours is qualitatively ambiguous.

Discussion Proposition 3 encompasses several motives for government redistribution that are explored theoretically and empirically in the literature. For example, Piketty (1995) discusses that an individual who believes that luck is the major determinant of economic success is expected to favor government redistribution; in contrast, an individual who believes in the importance of personal endeavor is expected to oppose redistribution. These motives are connected to the redistribution role for comparative advantage ("hard work") and the insurance role for productivity risk ("luck").

Deadweight loss due to the distortive tax is inherent in counteracting effects on hours worked (e.g., Sheshinski (1972); Meltzer and Richard (1981)). Since the model incorporates non-linear taxes, this papers nests discussions about deadweight loss in the existing literature, which is mainly up to linear taxes and lump-sum transfers.

Selection effects appear because of workers' occupational choices in the model. In the optimal tax studies, Rothschild and Scheuer (2013) characterize the optimal redistributive tax in the Roy model and argue that optimal progressivity is higher when occupational choice is present. In contrast, this paper incorporates in the quantitative model multiple roles of progressive taxes that are qualitatively counter-vailing and evaluates those forces through the lens of the model matched with linked micro data.

Bénabou and Ok (2001) show that under certain parametric conditions, prospects of upward mobility (POUM) reduce the demand for redistribution relative to the basic Meltzer-Richard case. Unlike the POUM hypothesis, the key mechanism in this paper is that for those who are exposed to technological change and expect benefits from this exposure. Hence, there is an incentive for skill investment while higher progressivity makes it more costly. As a result, two forms of skill investment considered in the model are negatively affected by progressive taxes. This key mechanism is discussed both qualitatively and quantitatively through the estimated model in Section 6.1.

5 Parametrization

In this section, I discuss parametriztion of the quantitative model. The model is parameterized with twelve demographic groups (age; gender; education), two types of equipment (non-ICT; ICT), six occupation groups (see Table A2), and four types of tasks: computer, social, manual, and routine. Age groups, occupation groups, types of tasks are identical to those in the empirical analysis, and types of equipment are extended with computer and non-computer related equipment.

Model parameters are chosen in two stages. In the first stage, I calibrate the parameters that can be set directly to their empirical counterparts without solving the model. I estimate the parameters directly from the data and use standard values from the literature. In the second stage, I estimate the political block using the maximum-likelihood method and minimizing the distance of the model and the data by solving the model.

5.1 External calibration

Here, I discuss parameters chosen in the first-stage. Table 3 summarizes the set of parameters that are externally calibrated.

Task importance To estimate task importance parameters by equipment and occupation α_{oes}, I construct a measure of the ICT usage rate from the APST data set, and Tools and Technology modules of the O*NET data set

$$\text{ICT Usage}_{ot} = \begin{cases} \frac{\sum_k \text{Mentions of Technology } k \text{ of job } j \text{ in occ } o}{\#\text{Job ads of job } j \text{ in occ } o} & :\text{APST} \\ \frac{\#\text{Technology Used of job } j \text{ in occ } o}{\#\text{All Types of Tools Used of job } j \text{ in occ } o} & :\text{O*NET} \end{cases} \tag{6}$$

where job j is defined as 3-digit Dorn's occupation code. To construct task intensity by occupations, tasks, and types of equipment, I use the predicted values

$$\widehat{\text{Task Intensity}}_{oest} = \hat{\beta}_s \widetilde{\text{ICT Usage}}_{oet} + \hat{\delta}_o, \quad \widetilde{\text{ICT Usage}}_{oet} = \begin{cases} \overline{\text{ICT Usage}}_{ot} & \text{if } e = \text{ICT} \\ 0 & \text{if } e = \text{non-ICT} \end{cases} \tag{7}$$

where $\overline{\text{ICT Usage}}_{ot}$ is the average ICT usage rate in occupation o in time t, which is from the regression below performed separately for each task type s, while controlling for relative importance to separate out effects from job posting and employment shares

$$\text{Task Intensity}_{ost} = \beta_s \text{ICT Usage}_{ot} + \gamma \text{Relative Imp}_{ot} + \delta_o + \eta_t + \epsilon_{oest}$$

where δ_o and η_t are occupation and time fixed effects. The predicted values are normalized up to the income share of labor $\bar{\alpha}_e \equiv \sum_s \alpha_{oes}$ to map from data to the model

$$\hat{\alpha}_{oest} = \bar{\alpha}_e \frac{\widehat{\text{Task Intensity}}_{oest}}{\sum_{s'} \widehat{\text{Task Intensity}}_{oes't}}$$

Equipment efficiency To obtain equipment efficiency q_e, I use the data set about quality-adjusted occupational capital prices, constructed by Caunedo et al. (2021). With this data set, I use the ICT usage rate in equation 6 to determine whether a 3-digit occupation is ICT intense or not.[19] Specifically, an occupation is defined as ICT-intense if its percentile of ICT usage rate is greater than the 50th percentile.

[19]The data set of Caunedo et al. (2021) is based on a slightly modified version of David Dorn's occupation code, updated by Deming (2017). For comparable linkage between their data set and the model, I made the occupation code in their data set consistent with David Dorn's code, and the information therein.

Table 3: Parameters calibrated externally

Parameter	Description	Source	Value
α_{oes}	Task importance	ICT usage rate, Regression equation 7	Table A3
π_g	Population shares	ACS	Table A4
ψ_g	Turnout rates	CPS-VOTE	Table A5
q_e	Equipment efficiency	Caunedo et al. (2021) dataset	Table A6
ξ	Labor elasticity	tax-adjusted Frisch elasticity	1.224
θ	Wage dispersion	Caunedo et al. (2021)	1.24
α_e	Equipment share	Burstein et al. (2013)	0.24
ρ	Demand elasticity	Burstein et al. (2019)	1.78
G	Govt. expenditures	Krusell and Rios-Rull (1999)	0.191

I compute the weighted average of ICT-intense occupational capital prices, where their Tornqvist quantities are used as weights. Since variables in their data set are normalized to the initial year, 2015 values in Table A6 are the efficiency relative to 1985 counterparts.

Population shares, turnout rates Population shares of demographic groups π_g are measured as employment shares from the ACS. For turnout rates I use the CPS-Voting and Registration Supplement (CPS-VOTE) dataset.[20]

Labor supply elasticity ξ is set such that tax-adjusted Frisch elasticity $\xi(1-\tau)$ is set to one. Benchmark τ is from Heathcote et al. (2020). Within-worker wage distribution across occupation-equipment pairs θ is from Caunedo et al. (2021). Elasticity of substitution across occupational goods ρ follow the value in Burstein et al. (2019).

Factor income share to both types of equipment is set to 0.24, referring to Burstein et al. (2013). Government expenditures as share of aggregate output is set to 0.191 as in Krusell and Rios-Rull (1999).

5.2 Internal calibration

Here, I discuss parameters chosen in the second stage. I estimate the political weight using the maximum-likelihood estimation and minimizing the distance between the model and the data at a given value of tax progressivity measured from data.[21] Table 4 summarizes parameters with solving the model.

[20] For the ACS, the sample includes individuals who are non-military employed, salary earners with positive real wages, usual hours worked greater than 260, ages 25 to 64, full time work status. For the CPS Voting and Registration Supplement, the same criteria are applied as long as the relevant information is available.

[21] The value of tax progressivity at which the distance is minimized is 0.186, referring to the estimated tax progressivity in Heathcote et al. (2020) from 1979 to 1983.

Political weight In this section, I describe how to estimate the political weight using stated preferences data. In the model, parameters of the predictable political preferences can vary over time. In mapping the model to data, I consider steady states.

Without loss of generality, consider that party L proposes more redistribution than the party R. Let ω_{gt} be the expected vote share backing party L in group g in time t.

$$\omega_{gt} = F_g\left(\Delta V_g - \eta_{ig} - \eta_i\right) = \Phi\left(-\sigma_{gt}^{-1}\left[\mu_{gt} + \eta_{ig} + \eta_i\right]\right)$$

where $\Delta V_g \equiv V_g\left(\lambda_L, \tau_L\right) - V_g\left(\lambda_R, \tau_R\right)$ is the utility differential when party L proposes a policy different from party R, and $\Phi(\cdot)$ is the cumulative distribution of the standard normal distribution. The second equality uses $\Delta V_g = 0$ since electoral equilibrium is symmetric. Inverting the vote share gives

$$\Phi^{-1}\left(\omega_{gt}\right) = -\sigma_{gt}^{-1}\left[\mu_{gt} + \eta_{ig} + \eta_i\right] \equiv \gamma_{gt}$$

where γ_{gt} the inverse-normal vote share backing party L in group g in time t. To arrive at an estimable equation, I extend the parametric approach in Stromberg (2008) by parametrizing the mean and variance of the predictable political preferences distribution as a function of observables: $\mu_{gt} = X_{1gt}\beta_\mu$ and $\sigma_{gt} = X_{2gt}\beta_\sigma$. The parameters $\beta_\mu, \beta_\sigma, \sigma_g, \sigma$ are estimated using a standard Maximum-Likelihood Estimation (MLE) of the above random-effects model. In MLE, election outcomes in all demographic groups contribute to the likelihood. Therefore, the joint log-likelihood function of $\gamma_t = \left(\gamma_{1t}, \cdots, \gamma_{Gt}\right)$ is

$$\begin{aligned}\log\mathcal{L}\left(\gamma_t\right) = -\frac{1}{2}\Bigg\{&\log\left(1 + \sum_g\left(\frac{\sigma}{\sigma_g}\right)^2\right) + \sum_g \log\left(\frac{\sigma_g}{\sigma_{gt}}\right)^2 \\ &+ G\log\left(2\pi\right) + \sum_g\left(\frac{\gamma_{gt}\sigma_{gt} + \mu_{gt}}{\sigma_g}\right)^2 - \sigma^2\frac{\left(\sum_g \frac{\left[\gamma_{gt}\sigma_{gt} + \mu_{gt}\right]}{\sigma_g^2}\right)^2}{1 + \sum_g\left(\frac{\sigma}{\sigma_g}\right)^2}\Bigg\}. \end{aligned} \tag{8}$$

Derivation of the joint log-likelihood function is available in Appendix B.5. After obtaining maximum-likelihood estimates $\hat{\beta}_\mu, \hat{\beta}_\sigma, \hat{\sigma}$, the estimated political weight of demographic group g is constructed by computing time average of $\hat{\omega}_{gt} = \phi\left(-\hat{\sigma}_{gt}^{-1}\hat{\mu}_{gt}\right)$, where ϕ is the probability density function of the standard normal distribution.[22]

Similarly as in the empirical study, I construct synthetic panel data of voter group g using redistribution, political spectrum, and controversial social issues (e.g., capital punishment)

[22] Given that the number of observations ($12 \times 6 = 72$) is limited in using the synthetic panel approach, I assume $\sigma_g = 1$ for accurate estimation.

Table 4: Paramaters calibrated internally

Parameter	Description	Moment	Value
H_g	Labor productivity	Post-tax real wage	Table A4
ω_g	Political weight	Stated preferences	Table A5
ϕ_o	Returns to time investment	Occupation employment share	Table A7
$\chi_{g=y}$	College education costs	Young college share ratio	1.0642, 1.4395
φ	Disutility of work	Employment-population ratio	1.4055

in GSS. For mapping the data to the model, I created a binary variable from redistribution preferences, in which one indicates "support redistribution" and zero otherwise.

Labor productivity, college costs, disutility of work For inherent labor productivity per demographic group H_g, the information of tax liability based on demographic characteristics is needed, because workers/voters' decisions are based on post-tax earnings. I use the NBER TAXSIM 35 to simulate net tax liability by submitting demographic characteristics as well as a variety of income variables at the CPS-ASEC.[23] The constructed taxes include: federal tax + state tax + half of the Federal Insurance Contributions Act (FICA) − Earned Income Tax Credit (EITC).[24] I then calculate relative post-tax wages per demographic group, having young/male/high school diploma as the reference group.

To pin down occupation-specific returns to time investment ϕ_o, I measure occupation employment shares from the ACS. I then calculate relative employment shares, having management/professionals as the reference group. The sample criteria are same as when measuring the population shares.

For counterparts of college education costs $\chi_{g=y}$, I measure young college employment shares from CPS-ASEC and calculate the ratio by gender. Costs for high school diploma is normalized to zero. Combined with post-tax wage different by demographic group, these college education costs are identified from labor productivity $H_g \times h^{\phi_o}$.

Employment-population ratio is measured from Federal Reserve Economic Data (FRED) to determine disutility of work φ. This value is 0.74 for 1978 to 1980.

[23] For the CPS-ASEC, the sample includes individuals who are non-military employed, salary earners with positive real wages, usual hours worked greater than 260, ages 25 to 64, full time work status, nominal wage exceeds a half of federal minimum wage, similar to criteria in Heathcote et al. (2010).

[24] I use the NBER TAXSIM Version 35. In the program, the calculated FICA tax includes both employee and employer portion, of which an employee only has to pay. For more details, refer to Feenberg and Coutts (1993) and the website http://users.nber.org/~taxsim/

Table 5: Model fit

Object	Description	Data	Value
τ	Tax progressivity	0.186	0.168
$\text{Var}(\log(w_g))$	Income Inequality	3.3455	2.4817

5.3 Model fit

The model generates equilibrium tax progressivity and earnings inequality per demographic group as untargeted moments. As a comparison, Heathcote et al. (2020) estimate tax progressivity from 1979 to 2016 and report tax progressivity of 0.186 for 1979 to 1983 and for 2012-2016. In my model the model-implied tax progressivity is 0.168, which is very close to their estimates. Measured post-tax earnings inequality from data, variance of log of post-tax earnings, is 3.3455. The model-implied inequality is 2.481.

The political-weight estimates do well in predicting the redistribution-share outcomes measured from the GSS. The average absolute error in demographic-group vote-forecasts is about 5%. This fit is comparable to the best results reported in the literature.[25]

Targeted parameters exactly match data and model-implied moments, which validates identification of estimated parameters that are calibrated internally.[26]

Overall, the model's performance of accounting for inequality and government redistribution is reasonably good. Table 5 summarizes the results discussed here.

6 Quantitative Results

Through the lens of the estimated model matched with micro data, I now investigate puzzling trends in aggregate: why have we observed lower tax progressivity despite the rise in income inequality? While the simple model of skill investment and government redistribution provides a hint through elevating concerns about efficiency stemming from skill investment, the full-fledged answer is yet to be seen.

To answer this question, I introduce underlying mechanisms governing preferences for government redistribution. Then I show that the model-generated trends in tax progressivity and inequality are consistent with those observed trends.

[25] Stromberg (2008) reports the average absolute error of 3%.

[26] The converged distance is less than 7.9619×10^{-18}.

6.1 Deciphering mechanism

Effects of government redistribution on skill accumulation From the worker's perspective, on the one hand, higher tax progressivity flattens income profiles of workers by increasing expected earnings of low-income workers and decreasing those of high-income workers. From the equation 5, the expected earnings reflects a worker's comparative advantage. The left panel in Figure 3 shows that after-tax (log) comparative advantage in utility units decreases as tax progressivity increases. Since workers accumulate skills by investing their (costly) time, this implies that higher progressivity makes skill investment more costly, which reduces their demand for redistribution.

From the young worker's viewpoint, whose skill composition is yet to be set in stone, higher tax progressivity reduces the incentive for costly college education because of the redistribution role for comparative advantage. This causes tension between costly college education and desires for government redistribution. The right panel in Figure 3 shows that a decrease in the choice probability of the young female is sharper than the young male as the progressivity rises. From Table 4, estimated college education costs of the young female are higher than the young male.[27] Therefore, unequal welfare effects imply that for the young female, progressivity decreases her incentive for skill investment more than it does for a young male worker.

At the group level, the potential efficiency losses from government redistribution are different by type of workers. For example, high-productivity workers are likely to lose more than what they would receive from government redistribution. This leads to differences in the most preferred policy of voter groups through affecting their welfare. This implies that policy stakes of voter groups are diverged and thus there are winners and losers from government redistribution.

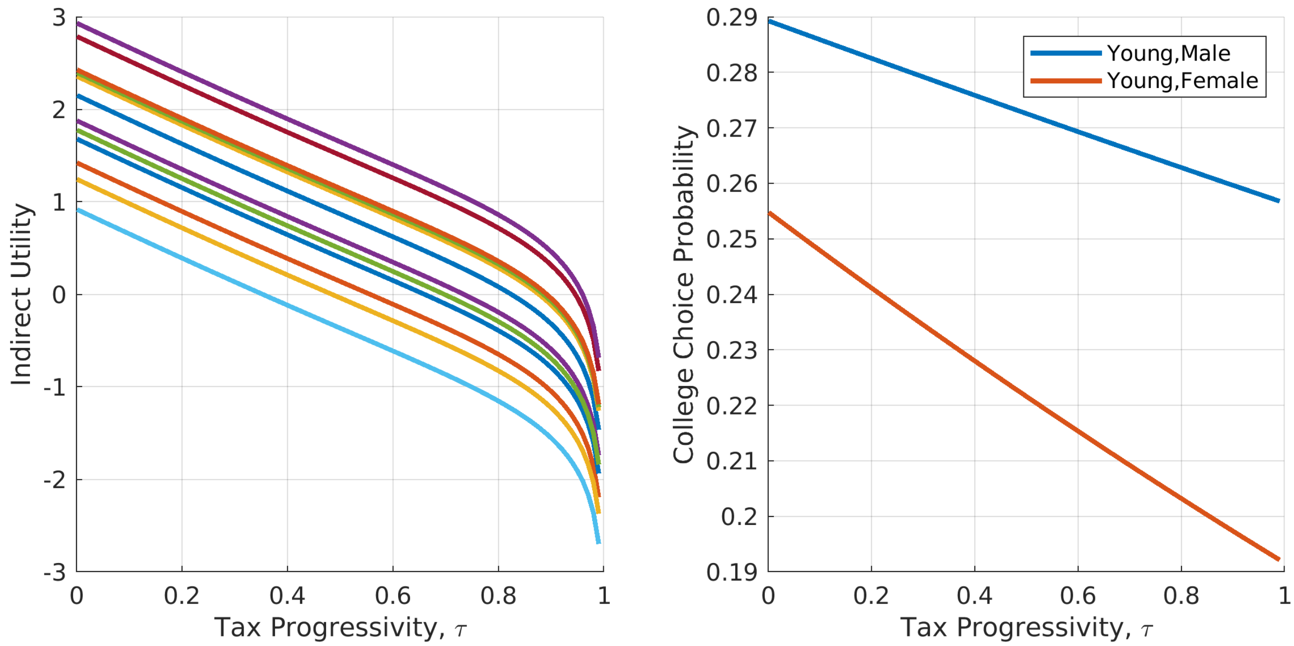
In the presence of the political channel – electoral competition – these policy stakes depend on the extent to which the group influences the political process.[28] Since politicians count the number of votes from groups and maximize their expected vote shares, it is crucial that workers must forecast how many potential colleagues consider the same policy stakes.

Role of elastic skill accumulation Using the simple model in Section 3, I showed that the gap of gains from lower tax progressivity is larger when the elasticity of skill investment

[27] This is consistent with the findings in the literature studying labor market distortions. For instance, Hsieh et al. (2019) find that the estimated "tax-wedge" is higher for women, in which the counterpart in my model is the college education costs.

[28] In this regard, the key difference between the "tax-wedge" approach and the political economy approach here is that distortions not just arise as an equilibrium outcome, but also reflect strategic competition among demographic groups trying to maximize their policy stakes.

Figure 3: Skill Accumulation and Tax Progressivity



Notes: Panel (left) displays log of the expected after-tax comparative advantage by demographic group (y-axis) as a function of tax progressivity (x-axis). Panel (right) displays the choice probabilities that a young worker attends college by gender (y-axis) as a function of tax progressivity (x-axis).

is higher. In the quantiative model in Section 6, the parameter ξ governs the elasticity of skill investment, since workers accumulate skill via learning-by-doing depending on work hours.

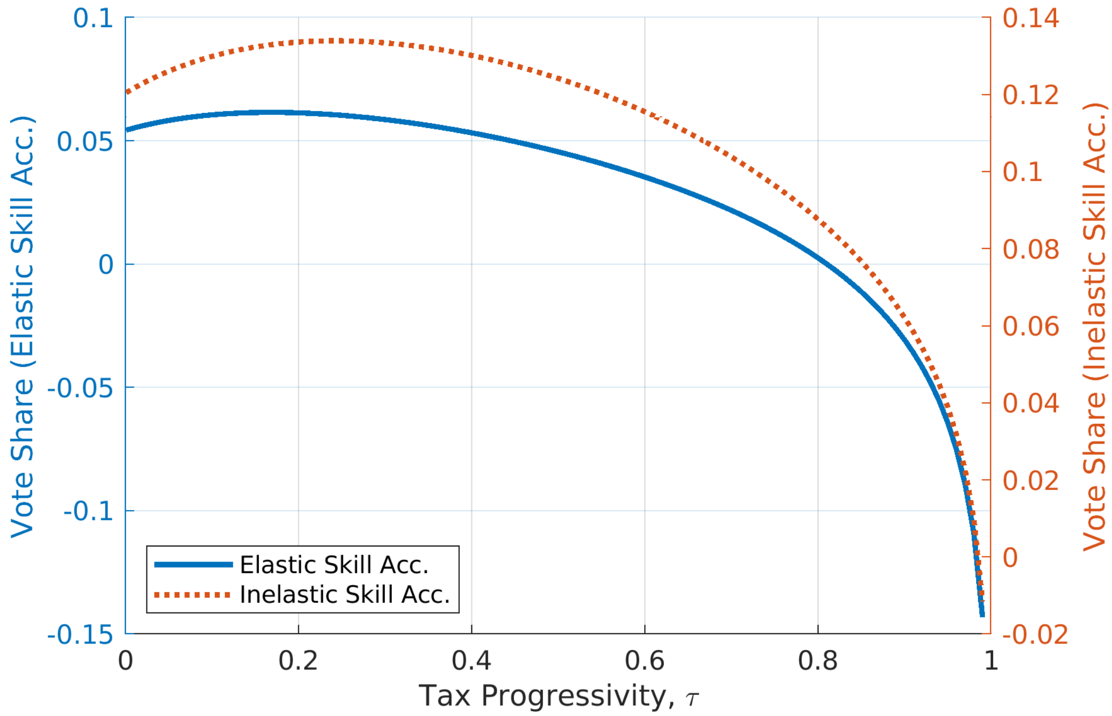
Figure 4 depicts the expected vote shares when the elasticity of work hours ξ is high and low. Equilibrium tax progressivity is 0.243 when ξ is 0.5. This tax progressivity of 0.243 is higher than than the progressivity of 0.168 when ξ is 1.224. Since the less elastically workers accumulate skills, their efficiency concerns decrease, and therefore costs of progressive tax is reduced. This confirms the intuition built in Proposition 1.

Policymaking processes I discuss differences in policymaking processes when (1) government policy is determined as a political outcome, and alternatively when (2) policymakers are considered as if they were the equal-weight utilitarian planner.

At the aggregate level, the mechanisms imply that in the policymaking process both the equity-efficiency trade-off and strategic concerns of voter groups are taken into consideration. It is the channel through which political clout of voter groups can influence the policymaking process, which is absent in an environment assuming an exogenous policy. Figure A2 shows that the expected vote share, an object political candidates care about, has different curvature from the social welfare function the utilitarian planner concerns.

The political equilibrium tax progressivity is lower than what the utilitarian planner

Figure 4: Vote Share - Elastic versus Inelastic Skill Accumulation



Notes: Figure displays the expected vote share when the elasticity of work hours is 1.224 (left y-axis) and the vote share when the elasticity is 0.5 (right y-axis) as a function of tax progressivity (x-axis). For more details about the expected vote share, see Proposition 2.

would choose to maximize the social welfare function. This *political wedge* arises because of the unequal weight that originates from the trade-off between voters' economic policy and political preferences, from the politician's viewpoint. This socio-economic tension in the political process interacts with equilibrium effects.

6.2 Technological change and tax progressivity

I now explore one of the main questions at beginning: what is the impact of computerization on inequality and tax progressivity? Up to this point, I have investigated the relationship of tax progressivity and efficiency concerns from skill accumulation, which shapes individual demand for redistribution, and policymaking processes that aggregate policy preferences.

I model computerization as a decline in equipment prices from 1985 to 2015. Utilizing the ICT usage rate measure in equation 6, estimated computer equipment prices reported in Table A6, have decreased more sharply than those of non-computer equipment. It is a reasonable description of computerization and capital-embodied technological change in general (Greenwood et al. (1997); Caunedo et al. (2021)).

Table 6: Technological Change, Income Inequality, and Tax Progressivity

		Inequality	Progressivity
Baseline calibration		2.4871	0.168
(1)	Change q_e	3.7726	0.168
(2)	Change q_e, $\omega_g = \psi_g = 1$	3.7340	0.173
(3)	Change q_e, $\phi_o = 1$	4.4944	0.259
(4)	Change q_e, $\omega_g = \psi_g = \phi_o = 1$	4.4526	0.265

Notes: Table shows comparative statistics of the quantitative model in Section 4. Case (1) changes the efficiency of equipment (q_e) from 1985 to 2015. Case (2) adds to Case (1) by setting the equal political weight on worker/voter groups (ω_g, ψ_g). Case (3) considers the equal occupation-specific returns to time investment (ϕ_o). Case (4) combines the second and third scenarios by setting the equal political weight and returns to time investment together.

Table 6 reports the results of the impacts of the decline in equipment prices on income inequality and tax progressivity, with and without considering the political policymaking process and skill accumulation of workers. The result of baseline calibration is reproduced to ease comparision of different counterfactual scenarios.

The case (1) considers the decline in equipment prices only. The model predicts that a sharp increase in income inequality, while tax progressivity remains unchanged. Qualitatively and quantiatively, this movement is consistent with non-increasing tax progressivity that empirical studies have documented. For example, Heathcote et al. (2020) reported that their measured tax progressivity has not changed between 1978-1980 and 2016-2018.

The case (2) examines the decline in equipment prices without unequal political weight (i.e., equal-weight utilitarian planner). Equivalently, this case turns off the strategic motive through which workers/voters affect the policymaking process because of the trade-off between economic policy preferences and social preferences from politicians' viewpoint. The resulting tax progressivity is slightly higher than in the case (1). Income inequality is also a bit lower according to the higher value of progressivity. In sum, the weight in a policymaking process does not drive the quantitative results largely, and the equal-weight utilitarian planner is more redistributive than the estimated political process.

The case (3) changes equipment prices from 1985 to 2015, with shutting down the skill accumulation channel by setting occupational returns to time investment equal to one. Both inequality and progressivity increase much for two reasons. First, efficiency costs from skill accumulation are absent, and therefore efficiency costs from progressive tax is much lower, which increases an equilibrium tax progressivity. This implies that in explaining observed tax progressivity, the quantitative role of the equity-efficiency trade-off is more sizeable than the that of the strategic motive. Second, skill accumulation could qualitatively either mitigate or aggaravate inequality. Quantitatively, it turns out that skill accumulation plays a role in mitigating inequality, and therefore inequality rises.

The case (4) combines exercises conducted in cases (1), (2), and (3). The results incorporate insights considered in those cases above. The equal weight social planner is more redistributive as in the case (2), which leads to somewhat higher tax progressivity. Resulting inequality is substantially greater than when skill accumulation is included as in the case (1). Taken together, the results are quantitatively similar to those in the case (3).

Overall, these counterfactual analyses confirm that skill accumulation channel is central to understand the movement in inequality and tax progressivity during the course of technological change through changes in individual policy preferences.

6.3 Robustness checks

In this section, I conduct robustness of the results by changing some parameters of the model. First, I consider changes in task importance from 1978-1980 to 2016-2018, estimated from the APST and the O*NET-OES data sets, respectively. Second, I set labor productivity per group H_g from estimates in Table A4 to one for all groups. Lastly, I change the government expenditures parameters from 0.191 to 0.259, in which the latter adds up the fraction of GDP spent in Social Security and Medicare as in Krusell and Rios-Rull (1999). Table 7 reports the results when different parameters are considered in the quantitative model.

Table 7: Robustness Checks

		Inequality	Progressivity
Baseline calibration		2.4871	0.168
(1)	Change α_{oes}	2.1202	0.178
(2)	Change $H_g = 1$	2.4871	0.168
(3)	Change $G = 0.259$	2.2324	0.168

The case (1) considers changes in task importance by occupation and equipment. Relative to the beginning of computerization in 1978-1980, importance of task types have been more equalized. The resulting progressivity is a little higher than the baseline, from 0.168 to 0.178, and inequality is slightly lower, from 2.4871 to 2.1202. This would reflect that as the use of new technologies becomes are more settled down, returns to investment in learning new technologies would have been lower, which would reduce efficiency costs of progressive tax.

The case (2) equalizes different labor productivity per demographic group by setting them one. Quantitatively, this would not change the results. Rather, this result buttresses that skill accumulation is quantitatively more important than inherent productivity differences across demographic groups.

The case (3) investigates whether higher fiscal pressure of financing government expenditures would change the result considerably. While the inequality is lower than the baseline, from 2.4871 to 2.2325, tax progressivity remains unchanged. Qualitative effects are ambiguous. On the one hand, higher fiscal pressure elevates concerns for efficiency to finance larger government expenditures. On the other hand, the increased government expenditures could also be used for redistribution. The result shows that the latter outweighs the former and the resulting inequality would be slightly lower.

7 Conclusion

This paper asks how technological change for the last four decades affects redistribution preferences at the micro level, and whether this is able to reconcile puzzling trends at the macro level: rising income inequality, non-increasing tax progressivity. The empirical study of this paper yields the first main finding: the computerization decreases individual preferences for redistribution, and this impact is meaningful even when occupational earnings are controlled for. To explain this novel finding, this paper develops a tractable quantitative general equilibrium model. The model demonstrates that returns to skill investment channel is the key to rationalize the empirical finding at the individual level, and reconcile the puzzling trends in aggregate.

In providing evidence to the micro-level question, the paper pioneers a novel approach connecting individual opinion, skill contents, and labor market outcomes to identify the impact of computerization on preferences for government redistribution. The developed model is a first macro political economy model by embedding technological change. In doing so, the fully-fledged model retains tractability enabling transparent mechanisms and quantitative exploration with rich heterogeneity.

This paper adds to the existing literature by connecting long-run structural change to the canonical political economy thought where individuals form their preferences for government policy and different policymaking process could imply differences in realized policies. At the individual level, technological change aggravates efficiency concerns in the presence of aspiration to accumulate skills. At the group level when policymaking process is influenced by voters with different policy interests, this causes a tension between skill investment and leaning to government redistribution, which depends on the extent of their relative political clout. In aggregate, these consideration may lead to the puzzling trends in inequality and government redistribution. One contribution of this paper is that it provides a quantitative answer to this qualitatively ambiguous question.

Given the applicability of approaches pioneered in this paper, the methodological contribution of this paper is to provide versatile tools to stimulate and investigate subsequent questions. For example, questions include exploring untapped policymaking processes and their socio-economic interaction with a variety of economic forces.

Finally, this paper is specialized to the United States. What is valid for one country would not be parallel to others. Considering massive heterogeneity across countries, the same analysis with different contexts within another country or cross-country studies should be conducted further.

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A Appendix - Tables and Figures

A.1 Additional Tables

Table A1: Descriptive Statistics: General Social Survey

Sample: ages 25-64	Mean	Standard Deviation
Demographics		
Age	42.01	10.68
Female	0.49	0.50
Married	0.64	0.48
White	0.78	0.41
Black	0.14	0.35
Other race	0.08	0.27
Work, Education		
Full time	0.53	0.50
High school dropout	0.13	0.33
High school diploma	0.49	0.50
Some college	0.07	0.26
College graduate	0.31	0.46
Years of Education	13.68	3.05
Political Identity		
Government redistribution	4.24	1.97
Political spectrum	3.90	1.38
Party affiliation	4.27	1.94
Observations	21312	

Notes: The table shows descriptive statistics of the General Social Survey from 1978 to 2018 with ages restricted to be between 25 and 64. College graduate includes post-college degree. The government redistribution (1-less redistribution, 7-more redistribution) is the answers recorded in 7-ordered integers. Similarly, political spectrum (1-Conservative, 7-Liberal), and party affiliation (1-Republican, 7-Democrat) are recorded.

Table A2: Occupation Groups

6 major groups	20 intermediate groups	Dorn's code
1. Management/Professionals	1. Management	[3,37]
	2. Architect, Engineers	[43,59]
	3. Computer, Math, Natural Science	[64,83]
	4. Healthcare Professionals	[84,106]
	5. Education, Library	[155,165]
	6. College Instructors, Social Science	154, [166,173]
	7. Legal and Social Services	[174,178]
	8. Art, Sports, Media	[183,199]
2. Technicians/Business/Finance	9. Technicians	[203,235]
	10. Finance, Business	[243,258]
3. Retail/Public Safety/Clerical	11. Retail Sales	[274,283]
	12. Public Safety, Administrative Support	[303,423]
4. Mechanics/Repairers/Production	13. Mechanics, Repairers	[503,549]
	14. Precision Production, Craft	[628,699]
5. Low-Skill Service Occupations	15. Cleaning, Food Preparation	[405,408], [433,444]
	16. Protection, Building Maintenance	[415,427]
	17. Leisure, Healthcare Support, Caring	[445,472]
6. Construction/Transport/Farming	18. Construction, Transportation	[558,599], [803,889]
	19. Machine Operators, Assemblers	[703,799]
	20. Agriculture, Farming, Mining	[473,498], [614,617]

*Notes: The table presents 6 broad and 20 occupations constructed from David Dorn's 3-digit occupation codes. Before constructing the occupation groups, Census Occupation Classification, Standard Occupation Classification, O*NET Taxonomy are harmonized at David Dorn's code.*

Table A3: Task Importance Estimates

Period: 1978-1980	Non-ICT equipment			
Occupations	Computer	Social	Manual	Routine
1. Management/Professionals	0.255	0.317	0.143	0.044
2. Technicians/Business/Finance	0.266	0.224	0.214	0.056
3. Retail/Public Safety/Clerical	0.145	0.313	0.205	0.097
4. Mechanics/Repairers/Production	0.028	0.381	0.323	0.028
5. Low-Skill Service Occupations	0.138	0.102	0.466	0.054
6. Construction/Transport/Farming	0.135	0.158	0.357	0.109
	ICT equipment			
Occupations	Computer	Social	Manual	Routine
1. Management/Professionals	0.354	0.261	0.107	0.037
2. Technicians/Business/Finance	0.420	0.162	0.137	0.041
3. Retail/Public Safety/Clerical	0.355	0.215	0.122	0.068
4. Mechanics/Repairers/Production	0.138	0.328	0.269	0.025
5. Low-Skill Service Occupations	0.188	0.094	0.428	0.051
6. Construction/Transport/Farming	0.251	0.132	0.286	0.091

Period: 2016-2018	Non-ICT equipment			
Occupations	Computer	Social	Manual	Routine
1. Management/Professionals	0.237	0.260	0.104	0.159
2. Technicians/Business/Finance	0.216	0.192	0.150	0.201
3. Retail/Public Safety/Clerical	0.208	0.183	0.142	0.226
4. Mechanics/Repairers/Production	0.139	0.184	0.204	0.233
5. Low-Skill Service Occupations	0.157	0.135	0.236	0.232
6. Construction/Transport/Farming	0.115	0.128	0.261	0.256
	ICT equipment			
Occupations	Computer	Social	Manual	Routine
1. Management/Professionals	0.243	0.256	0.103	0.158
2. Technicians/Business/Finance	0.225	0.187	0.148	0.200
3. Retail/Public Safety/Clerical	0.216	0.179	0.140	0.225
4. Mechanics/Repairers/Production	0.142	0.182	0.203	0.233
5. Low-Skill Service Occupations	0.160	0.134	0.235	0.231
6. Construction/Transport/Farming	0.120	0.126	0.259	0.255

Table A4: Population Shares (1978-1980) and Labor Productivity Estimates (1978-1980)

Demographic groups	Population shares (π_g)	Labor Productivity (H_g)
Young, Male, High school	0.1883	0.6004
Young, Female, High school	0.1451	0.3334
Young, Male, College	0.0743	0.7085
Young, Female, College	0.0464	0.4811
Middle, Male, High school	0.1342	0.7317
Middle, Female, High school	0.1071	0.2219
Middle, Male, College	0.0414	1.0026
Middle, Female, College	0.0194	0.4103
Old, Male, High school	0.1192	0.7503
Old, Female, High school	0.0867	0.2888
Old, Male, College	0.0266	1.1259
Old, Female, College	0.0113	0.4438

Table A5: Political Weight Estimates (1978-2018) and Voter Turnout Rates (1978-1980)

Demographic groups	Political weight (ω_g)	Turnout rates (ψ_g)
Young, Male, High school	0.0845	0.462
Young, Female, High school	0.0847	0.498
Young, Male, College	0.0837	0.752
Young, Female, College	0.0847	0.736
Middle, Male, High school	0.0836	0.613
Middle, Female, High school	0.0841	0.647
Middle, Male, College	0.0827	0.860
Middle, Female, College	0.0841	0.850
Old, Male, High school	0.0824	0.718
Old, Female, High school	0.0825	0.712
Old, Male, College	0.0803	0.890
Old, Female, College	0.0826	0.913

Table A6: Equipment Efficiency Estimates (1985, 2015)

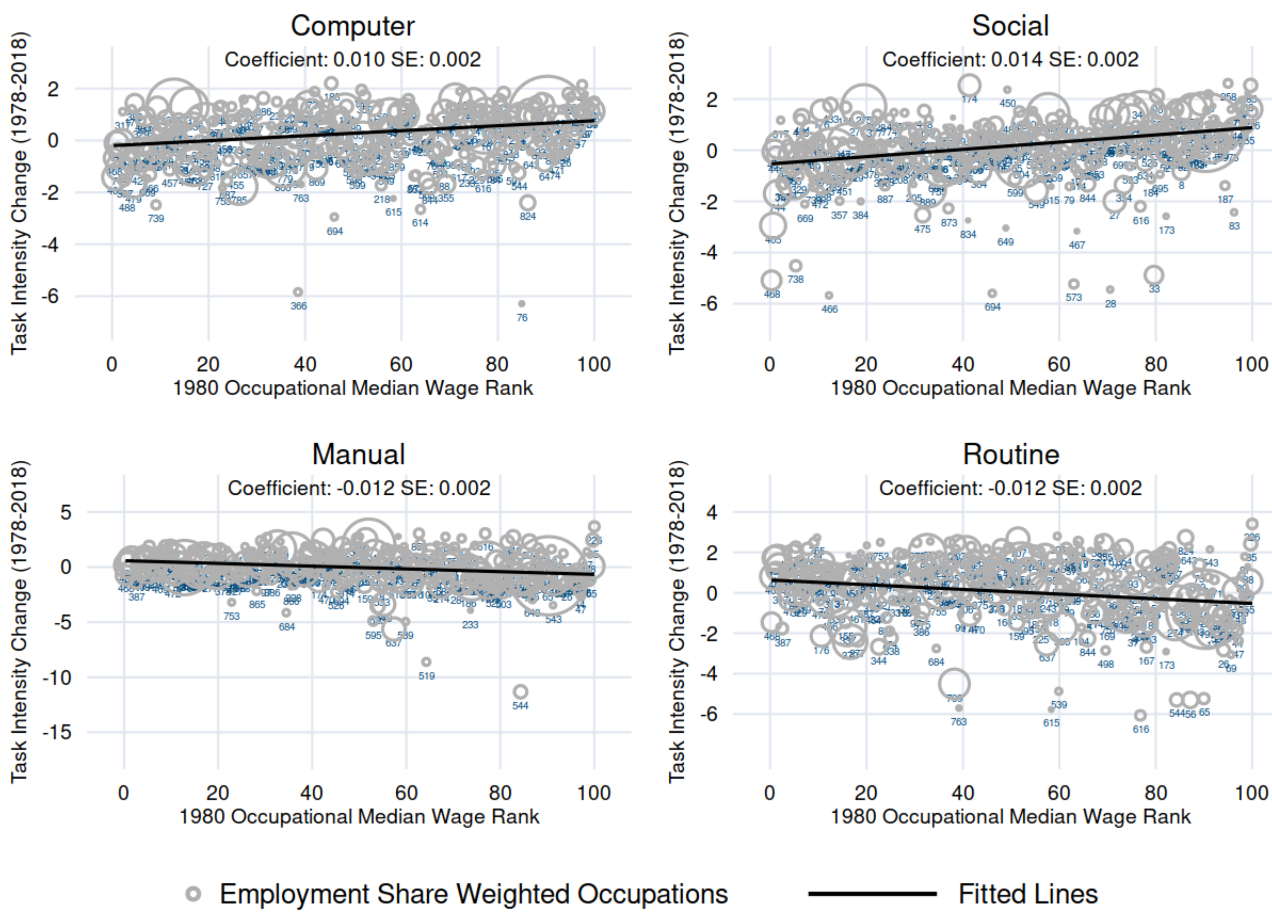
Equipment types	1985	2015
non-ICT	1	4.035
ICT	1	12.669

Table A7: Returns to Time Investment Estimates (1978-1980)

Occupations	Returns to Time Investment (ϕ_o)
1. Management/Professionals	-0.5177
2. Technicians/Business/Finance	10.7222
3. Retail/Public Safety/Clerical	0.1184
4. Mechanics/Repairers/Production	7.4999
5. Low-Skill Service Occupations	8.8092
6. Construction/Transport/Farming	-0.2747

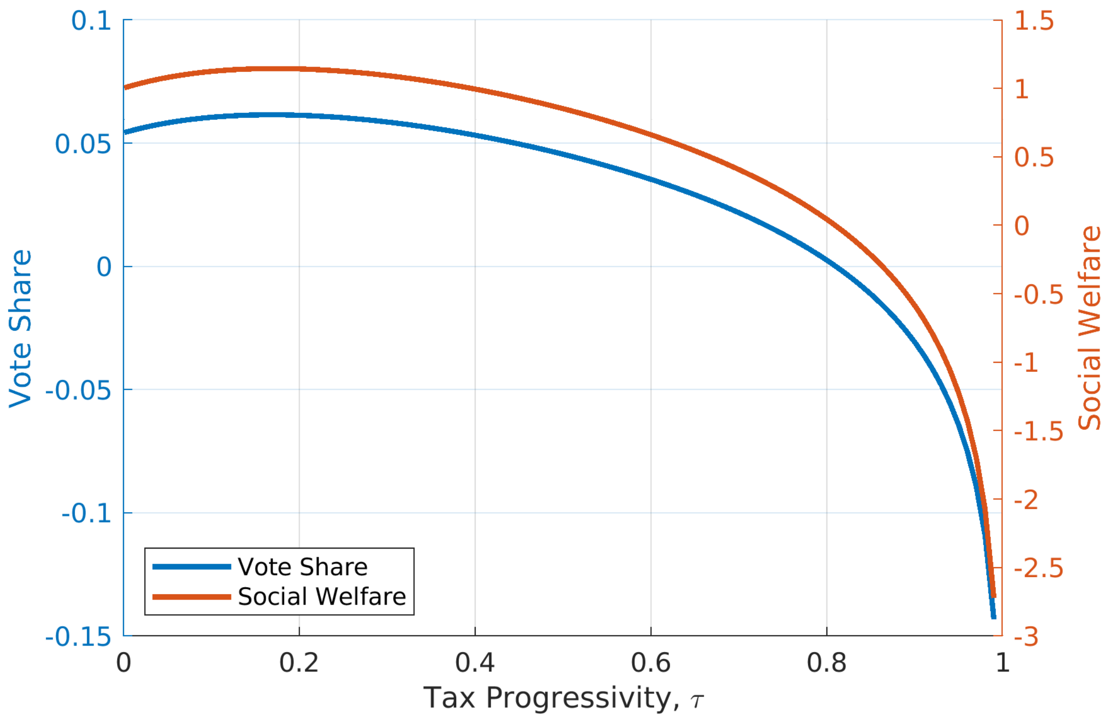
A.2 Additional Figures

Figure A1: Technological Change along the occupational wage distribution



*Notes: Clockwise panels display (x-axis) the changes in task intensities of computer, social, routine, and manual skills, respectively, measured from Atalay et al.'s (2020) and the O*NET-OES merged data (y-axis) along the occupational median wage distribution in 1980 measured from American Community Survey. The slope of regression lines indicates whether the changes in task intensities between 1978 and 2018 have been concentrated at higher or lower paying occupations. Circle sizes indicate the relative importance of occupations measured by job posting shares from Atalay et al.'s (2020) data set, and occupational employment shares from O*NET-OES merged data. For the results at 20 intermediate occupation groups see Figure 1.*

Figure A2: Vote Share and Social Welfare



Notes: Figure displays the expected vote share (left y-axis) and the social welfare function (right y-axis) as a function of tax progressivity (x-axis). For the expected vote share, see Proposition 2. The social welfare is of the equal-weight utilitarian planner.

B Appendix - Derivations and Proofs

B.1 Proof of Proposition 1

Assume $\varphi_{o'} - \varphi_o > 1$ for o, o' with $o \neq o'$, $\tau < \tau'$. A worker's utility maximization problem leads to indirect utilities up to a fiscal policy (λ, τ)

$$V\left(\lambda, \tau, q, \{\varphi_o\}_o, \kappa\right) = \max_{c,x} \left\{ \log c - \varphi_o \frac{x^{1+\frac{1}{\kappa}}}{1+\frac{1}{\kappa}} \quad s.t. \quad c = (1-\lambda)\left[x^q\right]^{1-\tau} \right\}$$

Substituting for consumption c in the utility function, the optimal skill investment x is obtained. Substitute for x in the utility function, indirect utilities up to a fiscal policy (λ, τ) are

$$x = \left[\frac{(1-\tau)\, q}{\varphi_o}\right]^{\frac{\kappa}{\kappa+1}} = \varphi_o^{\frac{-\kappa}{\kappa+1}} \left[(1-\tau)\, q\right]^{\frac{\kappa}{\kappa+1}}$$
$$V\left(\lambda, \tau, q, \{\varphi_o\}_o, \kappa\right) = \log(1-\lambda) + \frac{\kappa q (1-\tau)}{\kappa+1} \log\left[\frac{(1-\tau)\, q}{\varphi_o}\right] - \frac{\kappa q (1-\tau)}{\kappa+1}$$

Next, characterize the average level of post-earnings λ as a function of tax progressivity and other primitives. The fiscal budget constraint requires that net tax revenue must be zero. Using the optimal skill investment x leads to

$$\sum_o \pi_o (1-\lambda)\left[x^q\right]^{1-\tau} = \sum_o \pi_o x^q$$
$$(1-\lambda)\sum_o \pi_o \varphi_o^{\frac{-\kappa q(1-\tau)}{\kappa+1}} \left[(1-\tau)\, q\right]^{\frac{\kappa q(1-\tau)}{\kappa+1}} = \sum_o \pi_o \varphi_o^{\frac{-\kappa q}{\kappa+1}} \left[(1-\tau)\, q\right]^{\frac{\kappa q}{\kappa+1}}$$
$$1-\lambda = \frac{\sum_o \pi_o \varphi_o^{\frac{-\kappa q}{\kappa+1}} \left[(1-\tau)\, q\right]^{\frac{\kappa q}{\kappa+1}}}{\sum_o \pi_o \varphi_o^{\frac{-\kappa q(1-\tau)}{\kappa+1}} \left[(1-\tau)\, q\right]^{\frac{\kappa q(1-\tau)}{\kappa+1}}}$$

Substitute for the average level of post-tax earnings $(1-\lambda)$ in the utility function, indirect utilities are as a function of tax progressivity and primitives

$$V\left(\tau, q, \{\varphi_o\}_o, \kappa\right) = \log\sum_o \pi_o \varphi_o^{\frac{-\kappa q}{\kappa+1}} + \log\left[(1-\tau)\, q\right]^{\frac{\kappa q}{\kappa+1}} - \log\sum_o \pi_o \varphi_o^{\frac{-\kappa q(1-\tau)}{\kappa+1}} - \log\left[(1-\tau)\, q\right]^{\frac{\kappa q(1-\tau)}{\kappa+1}}$$
$$+ \frac{\kappa q (1-\tau)}{\kappa+1} \log\left[\frac{(1-\tau)\, q}{\varphi_o}\right] - \frac{\kappa q (1-\tau)}{\kappa+1}$$

Define $\Delta_\tau V_o \equiv V_{o,\tau} - V_{o,\tau'}$. Use the indirect utilities as a function tax progressivity above to characterize the utility gains from lower tax progressivity $\Delta_\tau V_o$

$$\begin{aligned}
\Delta_\tau V_o = & \frac{\kappa q}{\kappa+1}\log\left[\frac{1-\tau}{1-\tau'}\right] - \left[\log\sum_o \pi_o \varphi_o^{\frac{-\kappa q(1-\tau)}{\kappa+1}} - \log\sum_o \pi_o \varphi_o^{\frac{-\kappa q(1-\tau')}{\kappa+1}}\right] \\
& - \frac{\kappa q}{\kappa+1}\left[(1-\tau)\log(1-\tau) - \left(1-\tau'\right)\log\left(1-\tau'\right)\right] \\
& + \frac{\kappa q}{\kappa+1}\left[(1-\tau)\log\left[\frac{(1-\tau)\,q}{\varphi_o}\right] - \left(1-\tau'\right)\log\left[\frac{\left(1-\tau'\right)q}{\varphi_o}\right]\right] \\
& - \frac{\kappa q}{\kappa+1}\left[(1-\tau) - \left(1-\tau'\right)\right]
\end{aligned}$$

Similarly, define $\Delta_\tau V_{o'} \equiv V_{o',\tau} - V_{o',\tau'}$

$$\begin{aligned}
\Delta_\tau V_{o'} = & \frac{\kappa q}{\kappa+1}\log\left[\frac{1-\tau}{1-\tau'}\right] - \left[\log\sum_o \pi_o \varphi_o^{\frac{-\kappa q(1-\tau)}{\kappa+1}} - \log\sum_o \pi_o \varphi_o^{\frac{-\kappa q(1-\tau')}{\kappa+1}}\right] \\
& - \frac{\kappa q}{\kappa+1}\left[(1-\tau)\log(1-\tau) - \left(1-\tau'\right)\log\left(1-\tau'\right)\right] \\
& + \frac{\kappa q}{\kappa+1}\left[(1-\tau)\log\left[\frac{(1-\tau)\,q}{\varphi_{o'}}\right] - \left(1-\tau'\right)\log\left[\frac{\left(1-\tau'\right)q}{\varphi_{o'}}\right]\right] \\
& - \frac{\kappa q}{\kappa+1}\left[(1-\tau) - \left(1-\tau'\right)\right]
\end{aligned}$$

Characterize the utility differential across occupations o, o' $\Delta_\tau V_o - \Delta_\tau V_{o'}$ using $\Delta_\tau V_o$ and $\Delta_\tau V_{o'}$ above, respectively. After manipulating some algebra, the utility differential is

$$\Delta_\tau V_o - \Delta_\tau V_{o'} = \frac{\kappa q}{\kappa+1}\log\left[\varphi_{o'} - \varphi_o\right]\left[\tau' - \tau\right]$$

where $\Delta_\tau V_o - \Delta_\tau V_{o'} > 0$ holds by the assumption $\tau < \tau'$ and $\varphi_{o'} - \varphi_o > 1$. This completes the proof for the first result in Proposition 1. Using the first result, it is straightforward to show the second result in Proposition 1.

B.2 Proof of Proposition 2

Expected vote share In an election stage, a voter/worker with economic and political preferences i from demographic group g will vote for the party L if

$$V_g(\lambda_L, \tau_L) - V_g(\lambda_R, \tau_R) \equiv \Delta V_g \geq R_{igt} + \eta_{ig} + \eta_i$$

where $\Delta V_g = \Delta V_g\{(\lambda_L, \tau_L), (\lambda_R, \tau_R)\}$ is utility differential by policy proposals and $V_g(\lambda_x, \tau_x)$ is expected indirect utilities up to a policy proposal (λ_x, τ_x). Write for the predictable part of political preferences R_{igt}

$$R_{igt} \leq \Delta V_g - \eta_{ig} - \eta_i$$

The vote share that candidate L receive in demographic group g in an election, when the candidates have chosen strategies resulting in ΔV_g, and after the swings η_{ig} and η_i have been realized is obtained by integrating the mass above the cutoff point over the predictable preferences

$$F_g(\Delta V_g - \eta_{ig} - \eta_i)$$

where F_g is the cumulative distribution of the predictable preferences R_{igt}. Note that only ψ_g fraction of voters participates in an election (i.e., turnout), and each group has relative population share π_g. The number of votes backing the party L from demographic group g

$$\psi_g \pi_g F_g(\Delta V_g - \eta_{ig} - \eta_i)$$

The total votes backing the party L is the sum of the votes across all demographic groups. Under majority rule, the party L wins an election if the total votes backing the party L exceed a half of the effective electorate who actually come to polling places

$$\sum_g \psi_g \pi_g \{(\lambda_L, \tau_L), (\lambda_R, \tau_R)\} F_g(\Delta V_g - \eta_{ig} - \eta_i) \geq \frac{1}{2} \sum_g \psi_g \pi_g \{(\lambda_L, \tau_L), (\lambda_R, \tau_R)\}$$

Denote the total votes of the party L, the left-hand side, as $T_L\{(\lambda_L, \tau_L), (\lambda_R, \tau_R)\}$. Both parties are assumed to maximize their expected vote shares. Since the effective electorate is constant, it is a constant-sum game. That is,

$$T_L\{(\lambda_L, \tau_L), (\lambda_R, \tau_R)\} + T_R\{(\lambda_L, \tau_L), (\lambda_R, \tau_R)\} = \sum_g \psi_g \pi_g \{(\lambda_L, \tau_L), (\lambda_R, \tau_R)\}$$

The proof of symmetry which follows immediately constructs a symmetric constant-sum game. Therefore, the parties L maximizes their expected vote share

$$\sum_g \psi_g \pi_g \{(\lambda_L, \tau_L), (\lambda_R, \tau_R)\} F_g(0) V_g(\lambda_L, \tau_L)$$

Proof of symmetry Suppose the party L proposes a different policy $(\lambda_L, \tau_L) \neq (\lambda_R, \tau_R)$, so total votes of respective parties are different, i.e., $T_L \neq T_R$. Without loss of generality, let $T_L < T_R$. This leads to

$$\begin{aligned} T_L &< T_R \\ T_L + T_L &< T_L + T_R \\ T_L + T_L &< \sum_g \psi_g \pi_g \end{aligned}$$

where the last inequality $T_L < \frac{1}{2} \sum_g \psi_g \pi_g$ contradicts the best-response rule of the party L, $T_L \geq \frac{1}{2} \sum_g \psi_g \pi_g$, which must hold in an election. Therefore, Nash equilibrium in an election is symmetric. Applying symmetry leads to the equation in Proposition 2.

B.3 Proof of Proposition 3

Let $m, n = (o, e)$ be arbitrary occupation-equipment choice pairs, where $m \neq n$. A choice-specific value of an individual i in demographic group g is defined as

$$V_{img} \equiv \max_{m \neq n} \left\{ \log \left[(1-\lambda) \left(P_{mg} h_i \epsilon_{im} \right)^{1-\tau_x} \right] - \varphi \frac{h_i^{1+\frac{1}{\xi}}}{1+\frac{1}{\xi}} > \log \left[(1-\lambda) \left(P_{ng} h_i \epsilon_{in} \right)^{1-\tau_x} \right] - \varphi \frac{h_i^{1+\frac{1}{\xi}}}{1+\frac{1}{\xi}} \right\}$$

Note the optimal hours worked h^* is independent of m. Without loss of generality, I drop the subscript for political party $x \in \{L, R\}$, and let $H = \varphi \frac{(h^*)^{1+\frac{1}{\xi}}}{1+\frac{1}{\xi}}$ for notational convenience.

Due to i.i.d. idiosyncratic productivity, V_{img} is a random variable, which possesses the cumulative distribution $\Pr(V_{img} < x)$. This cumulative distribution function is

$$\begin{aligned}
\Pr(V_{img} < x) &= \Pr \left\{ \epsilon_{im} < e^{\frac{x + H - \log(1-\lambda) P_{mg}^{1-\tau} (h^*)^{1-\tau}}{1-\tau}} \right\} \times \Pr \left\{ \epsilon_{in} < e^{\frac{x + H - \max_{n \neq m} \left[\log(1-\lambda) P_{mg}^{1-\tau} (h^*)^{1-\tau} \right]}{1-\tau}} \right\} \\
&= \Pr \left\{ \epsilon_{im} < \frac{e^{\frac{x}{1-\tau}} e^{\frac{H}{1-\tau}}}{(1-\lambda)^{\frac{1}{1-\tau}} P_{mg} (h^*)} \right\} \times \Pr \left\{ \epsilon_{in} < \frac{e^{\frac{x}{1-\tau}} e^{\frac{H}{1-\tau}}}{\max_{n \neq m} (1-\lambda)^{\frac{1}{1-\tau}} P_{ng} (h^*)} \right\} \\
&= e^{-\left[\frac{e^{\frac{x}{1-\tau}} e^{\frac{H}{1-\tau}}}{(1-\lambda)^{\frac{1}{1-\tau}} P_{mg}(h^*)} \right]^{-\theta}} \times e^{-\left[\frac{e^{\frac{x}{1-\tau}} e^{\frac{H}{1-\tau}}}{\max_{n \neq m} (1-\lambda)^{\frac{1}{1-\tau}} P_{ng}(h^*)} \right]^{-\theta}}
\end{aligned}$$

where the second equality uses properties of logarithm and the last equality uses the definition of the Frechet marginal distribution with the shape parameter θ. Use properties of exponents to write

$$\Pr(V_{img} < x) = e^{-\left[e^{-\left\{ \frac{x - \left[\log(1-\lambda) P_{mg}^{1-\tau} (h^*)^{1-\tau} - H \right]}{\frac{1-\tau}{\theta}} \right\}} \right]} \times e^{-\left[e^{-\left\{ \frac{x - \left[\max_{n \neq m} \log(1-\lambda) P_{ng}^{1-\tau} (h^*)^{1-\tau} - H \right]}{\frac{1-\tau}{\theta}} \right\}} \right]}$$

Let $\tilde{\tau} = \frac{1-\tau}{\theta}$ and $A_m = \log(1-\lambda) P_{mg}^{1-\tau} (h^*)^{1-\tau}$ and A_n similarly for notational brevity. The cumulative function above is of the Gumbel with the scale $\tilde{\tau}$ and the location $\tilde{\tau} \log \left[e^{\sum_{n=1}^{M} \frac{A_n}{\tilde{\tau}}} \right] - H$. Indirect utilities up to policy are the expected value of the random variable V_{img}. Calculating this first moment amounts to using the moment-generating function of the Gumbel distribution. Namely,

$$V_g \equiv \mathbb{E}_\epsilon \left[\max_{im} V_{img} \right] = \left(\frac{1-\tau}{\theta} \right) \times \log \left[\sum_m (1-\lambda)^{\frac{\theta}{1-\tau}} P_{mg}^{\theta} (h^*)^{\theta} \right] - H^* + \frac{\gamma_{em}}{\theta} (1-\tau)$$

where $h^* = \left(\frac{1-\tau}{\varphi} \right)^{\frac{\xi}{1+\xi}}$, $H^* = (1-\tau) \frac{\xi}{1+\xi}$, and $\gamma_{em} = 0.5772156\ldots$ is the Euler-Mascheroni constant as a result of the integration. After manipulating some algebra, the expression above is identical to the equation in Proposition 3.

B.4 Derivation of equilibrium characterization

This section provides derivations of analytical expressions of the equations 3, 4, and 5 in the Subsection 4.4: characterization - partial equilibrium.

Price per efficiency hour units Let $m = (o, e)$ be an arbitrary occupation-equipment choice pair. The profit maximization problem of production-unit firms is

$$\max_{k_e, n_g} P_o \prod_s (T_{mgs})^{\alpha_{ms}} k_e^{1-\bar{\alpha}_e} - P_{mg} n_g - P_e k_e$$

where $T_{mgs} = H_g \times h^{\phi_o} \times l_{mgs}$, $\sum_s l_{mgs} = h^*$, and $\bar{\alpha}_e = \sum_s \alpha_{ms}$. Obtain the first-order necessary condition with respect to the units of type-e equipment k_e and substitute for k_e in the expression above, the output of a production unit can be written as

$$Y_{mg} = \prod_s \left(H_g h^{\phi_o} l_{mgs} \right)^{\frac{\alpha_{ms}}{\bar{\alpha}_e}} \left\{ \frac{P_o}{P_e} (1 - \bar{\alpha}_e) \right\}^{\frac{1-\bar{\alpha}_e}{\bar{\alpha}_e}}$$

Note that in equilibrium the profit-maximization problem of type-e equipment producers leads to prices per type-e equipment $P_e = q_e^{-1}$. Moreover, the profit-maximizing production unit firm distribute hours across types of tasks $l_{mgs} = \left(\frac{\alpha_{ms}}{\bar{\alpha}_e} \right) h^*$. Substitute for P_e and l_{mgs} in the expression

$$P_{mg} = \bar{\alpha}_e (1 - \bar{\alpha}_e)^{\frac{1-\bar{\alpha}_e}{\bar{\alpha}_e}} P_o^{\frac{1}{\bar{\alpha}_e}} q_e^{\frac{1-\bar{\alpha}_e}{\bar{\alpha}_e}} \left\{ \prod_s \left(H_g (h^*)^{\phi_o} \frac{\alpha_{ms}}{\bar{\alpha}_e} h^* \right)^{\frac{\alpha_{ms}}{\bar{\alpha}_e}} \right\}$$

where $h^* = \left(\frac{1-\tau}{\varphi} \right)^{\frac{\xi}{1+\xi}}$ holds in from the worker's utility maximization problem. After manipulating some algebra, the expression above is identical to the equation 3.

Occupation-equipment pair choice probability Let $m, n = (o, e)$ be arbitrary occupation-equipment choice pairs, where $m \neq n$. Probability that a worker from demographic group g chooses m is defined as

$$\pi_{mg} = \Pr \left\{ \log (1 - \lambda) (P_{mg} h_i \epsilon_{im})^{1-\tau_x} - \varphi \frac{h_i^{1+\frac{1}{\xi}}}{1 + \frac{1}{\xi}} > \max_{n \neq m} \log (1 - \lambda) (P_{ng} h_i \epsilon_{in})^{1-\tau_x} - \varphi \frac{h_i^{1+\frac{1}{\xi}}}{1 + \frac{1}{\xi}} \right\}$$

Since the optimal hours worked h^* is independent of m because of the property of log preferences that income and substitution effects are offset exactly, disutility from hours worked is canceled out both sides of the inequality.

Without loss of generality, I drop the subscript for political party $x \in \{L, R\}$ for notational convenience. The choice probability can be written as

$$\begin{aligned}\pi_{mg} &= \Pr\left[\epsilon_{in} < \left(\frac{P_{mg}}{P_{ng}}\right)\epsilon_{im} \quad \forall n \neq m\right] \\ &= \int_0^\infty \exp\left\{-\epsilon_{im}^{-\theta}\sum_{n=1}^{M}\left(\frac{P_{ng}}{P_{mg}}\right)^\theta\right\}\exp\left\{-\epsilon_{im}^{-\theta}\right\}\exp\left\{\epsilon_{im}^{-\theta}\right\}\theta\epsilon_{im}^{-1-\theta}d\epsilon_{im}\end{aligned}$$

where the second equality uses the i.i.d. property and the probability density function of the Frechet marginal distribution with the shape parameter θ.

Define $\sum_{n=1}^{M}\left(\frac{P_{ng}}{P_{mg}}\right)^\theta = \Sigma_{mg}$ and $u = -\epsilon_{im}\Sigma_{mg}$ for the change-of-variable technique. After manipulating some algebra, the choice probability can be written as identical to the equation 4

$$\pi_{mg} = \int_0^\infty e^u du\left[\frac{1}{\Sigma_{mg}}\right] = \frac{1}{\sum_{n=1}^{M}\left(\frac{P_{ng}}{P_{mg}}\right)} = \frac{P_{mg}^\theta}{\sum_{n=1}^{M}P_{ng}^\theta}.$$

Expected earnings Let $m, n = (o, e)$ be arbitrary occupation-equipment choice pairs, where $m \neq n$. Without loss of generality, I drop the subscript for political party $x \in \{L, R\}$. The expected earnings of a worker in demographic group g is

$$w_{mg} = (1-\lambda)\left(P_{mg}h^*\right)^{1-\tau}\mathbb{E}_\epsilon\left[\epsilon_{im}^{1-\tau}|i \in \Omega_{mg}\right]$$

where $\mathbb{E}_\epsilon\left[\epsilon_{im}^{1-\tau}|i \in \Omega_{mg}\right]$ is the expected efficiency per hour supplied from a worker i who selects m, and the set Ω_{mg} is the set of workers who choose m, i.e.,

$$\Omega_{mg} = \left\{i|\log\left[(1-\lambda)\left(P_{mg}h_i\epsilon_{im}\right)^{1-\tau}\right] - \varphi\frac{h_i^{1+\frac{1}{\xi}}}{1+\frac{1}{\xi}} > \log\left[(1-\lambda)\left(P_{ng}h_i\epsilon_{in}\right)^{1-\tau}\right] - \varphi\frac{h_i^{1+\frac{1}{\xi}}}{1+\frac{1}{\xi}} \quad \forall n \neq m\right\}$$

Characterizing the expected earnings w_g amounts to characterizing the expected efficiency per hour supplied from a worker i who selects m. Let $F_\epsilon(\epsilon_{im})$ is the cumulative distribution function of the Frechet marginal with the shape parameter θ. This expected value is expressed as

$$\begin{aligned}\mathbb{E}\left[\epsilon_{im}^{1-\tau}|i \in \Omega_{mg}\right] &= \frac{1}{\pi_{mg}}\int_0^\infty \epsilon^{1-\tau}\Pr\left\{\log\left[(1-\lambda)\left(P_{mg}h_i\epsilon_{im}\right)^{1-\tau}\right] - \varphi\frac{h^{1+\frac{1}{\xi}}}{1+\frac{1}{\xi}}\right. \\ &\left. > \max_{n\neq m}\log\left[(1-\lambda)\left(P_{ng}h_i\epsilon_{in}\right)^{1-\tau}\right] - \varphi\frac{h^{1+\frac{1}{\xi}}}{1+\frac{1}{\xi}} \quad \forall n \neq m\right\}dF_\epsilon(\epsilon_{im}) \\ &= \frac{1}{\pi_{mg}}\int_0^\infty \epsilon^{1-\tau}\times\exp\left\{-\epsilon_{im}^{-\theta}\sum_{n=1}^{M}\left(\frac{P_{ng}}{P_{mg}}\right)^\theta\right\}\exp\left\{-\epsilon_{im}^{-\theta}\right\}\exp\left\{\epsilon_{im}^{-\theta}\right\}\theta\epsilon_{im}^{-1-\theta}d\epsilon_{im}\end{aligned}$$

Define $\sum_{n=1}^{M}\left(\frac{P_{ng}}{P_{mg}}\right)^{\theta}=\Sigma_{mg}$ and $u=\epsilon_{im}^{-\theta}\Sigma_{mg}$ for the change-of-variable technique. Let $\tilde{\tau}=1-\tau$ for notational convenience. After manipulating some algebra, the expected value is

$$\begin{aligned}
\mathbb{E}\left[\epsilon_{im}^{1-\tau}|i\in\Omega_{mg}\right] &= \frac{1}{\pi_{mg}}\int_{0}^{\infty}\exp\left\{-\epsilon_{im}^{-\theta}\sum_{n=1}^{M}\left(\frac{P_{ng}}{P_{mg}}\right)^{\theta}\right\}\theta\epsilon_{im}^{-1-\theta+\tilde{\tau}}d\epsilon_{im} \\
&= \frac{1}{\pi_{mg}}\int_{-\infty}^{0}\exp\left\{-u\right\}\Sigma_{mg}^{\frac{\tilde{\tau}}{\theta}}u^{-\frac{\tilde{\tau}}{\theta}}\frac{1}{\Sigma_{mg}}\left(-du\right) \\
&= \Sigma_{mg}^{\frac{\tilde{\tau}}{\theta}}\int_{0}^{\infty}\exp\left\{-u\right\}u^{-\frac{\tilde{\tau}}{\theta}}du \\
&= \Sigma_{mg}^{\frac{\tilde{\tau}}{\theta}}\Gamma\left(1-\frac{\tilde{\tau}}{\theta}\right)
\end{aligned}$$

where the last inequality uses $\pi_{mg}=\Sigma_{mg}^{-1}$, and the definition of the Gamma function which reads

$$\Gamma\left(\eta\right)\equiv\int_{0}^{\infty}t^{\eta-1}\exp\left(-t\right)dt$$

where η is a positive real number. Using the expression for the expected efficiency per hour supplied from a worker i who selects m, $\mathbb{E}\left[\epsilon_{im}^{1-\tau}|i\in\Omega_{mg}\right]$, the expected earnings is

$$\begin{aligned}
w_{mg} &= \left(1-\lambda\right)\left(P_{mg}h^{*}\right)^{1-\tau}\Gamma\left(1-\frac{1-\tau}{\theta}\right)\left(\frac{1}{\pi_{mg}}\right)^{\frac{1-\tau}{\theta}} \\
&= \left(1-\lambda\right)\left(P_{mg}h^{*}\right)^{1-\tau}\Gamma\left(1-\frac{1-\tau}{\theta}\right)\frac{\left\{\sum_{n=1}^{M}P_{ng}^{\theta}\right\}^{\frac{1-\tau}{\theta}}}{P_{mg}^{1-\tau}} \\
&= \left(1-\lambda\right)\left(\frac{1-\tau}{\varphi}\right)^{\frac{\xi(1-\tau)}{1+\xi}}\Gamma\left(1-\frac{1-\tau}{\theta}\right)\left\{\sum_{n=1}^{M}P_{ng}^{\theta}\right\}^{\frac{1-\tau}{\theta}}
\end{aligned}$$

where the second equality uses $\pi_{mg}=\Sigma_{mg}^{-1}$ and the last equality uses the optimal hours worked h^{*}. This expression is identical to the equation 5.

B.5 Derivation of the joint log-likelihood function

This section provides a detailed derivation of the analytical expression of the joint log-likelihood function in the equation 8 in the Subsection 5.2: internal calibration.

Joint log-likelihood function In equilibrium, both candidates choose the same allocation, so that $\Delta V_g = 0$ in all groups. The vote share backing party L in group g at time t is

$$\begin{aligned} \omega_{gt} = F_g\left(-\eta_{ig} - \eta_i\right) = \Phi\left(-\sigma_{gt}^{-1}\left[\mu_{gt} + \eta_{ig} + \eta_i\right]\right) \\ \Phi^{-1}\left(\omega_{gt}\right) = -\sigma_{gt}^{-1}\left(\mu_{gt} + \eta_{ig} + \eta_i\right) \equiv \gamma_{gt} \end{aligned}$$

Conditional on aggregate swings η_i, the group-specific swings in a group γ_{gt} follows the normal distribution with mean $-\sigma_{gt}^{-1}\left[\mu_{gt} + \eta_{ig} + \eta_i\right]$ and the standard deviation σ_g/σ_{gt}. Namely,

$$h\left(\gamma_{gt}|\eta_i\right) = \frac{1}{\sqrt{2\pi}\left(\frac{\sigma_g}{\sigma_{gt}}\right)} \exp\left(-\frac{1}{2}\left[\frac{\gamma_{gt} + \frac{1}{\sigma_{gt}}\left(\mu_{gt} + \eta_i\right)}{\left(\frac{\sigma_g}{\sigma_{gt}}\right)}\right]^2\right)$$

where h is the associated density function conditional on aggregate swings η. For notational brevity in what follows, define the variables: $\hat{z}_{gt} = \gamma_{gt} + \mu_{gt}/\sigma_{gt}$, $\hat{\eta} = \eta_i/\sigma_g$, and $\hat{\sigma}_g = \sigma_g/\sigma_{gt}$.

Conditional on aggregate swings η_i, the joint likelihood of election outcomes in all groups $\gamma_t = (\gamma_{1t}, \cdots, \gamma_{Gt})$ is the product of group-specific swings in all groups

$$h\left(\gamma_t|\eta_i\right) = \prod_g h\left(\gamma_{gt}|\eta_i\right) = \prod_g \frac{1}{\sqrt{2\pi}\hat{\sigma}_g} \exp\left(-\frac{1}{2}\left[\frac{\hat{z}_{gt} + \hat{\eta}}{\hat{\sigma}_g}\right]^2\right)$$

The unconditional likelihood is obtained by integrating over all potential outcomes of aggregate swings η_i. The integration of $h\left(\gamma_t|\eta_i\right)$ leads to

$$h\left(\gamma_t\right) = \int_{-\infty}^{\infty} \prod_g \frac{1}{\sqrt{2\pi}\hat{\sigma}_g} \exp\left(-\frac{1}{2}\left[\frac{\hat{z}_{gt} + \hat{\eta}}{\hat{\sigma}_g}\right]^2\right) \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{1}{2}\frac{\eta^2}{\sigma^2}\right) d\eta$$

where subscript i drops in what follows for notational brevity. After manipulating some algebra, the unconditional likelihood can be rewritten as

$$h\left(\gamma_t\right) = \frac{1}{\sqrt{2\pi}\sigma} \prod_g \frac{1}{\sqrt{2\pi}\hat{\sigma}_g} \int_{-\infty}^{\infty} \exp\left(-\frac{1}{2}\left\{\sum_g \left[\frac{\hat{z}_{gt} + \hat{\eta}}{\hat{\sigma}_g}\right]^2 + \frac{\eta^2}{\sigma^2}\right\}\right) d\eta \tag{9}$$

Obtaining a closed-form expression amounts to evaluating this integral. Define an auxilary variable to make it clear in what follows

$$\frac{1}{\omega^2} \equiv \frac{1}{\sigma^2} + \sum_g \frac{1}{\sigma_g^2}$$

Terms in the curly bracket $\left\{\sum_g \left[\frac{\hat{z}_{gt}+\hat{\eta}}{\hat{\sigma}_g}\right]^2 + \frac{\eta^2}{\sigma^2}\right\}$ can be simplifed by completing the square in η

$$
\begin{aligned}
&= \sum_g \frac{\hat{z}_{gt}^2 + 2\hat{z}_{gt}\hat{\eta} + \hat{\eta}^2}{\hat{\sigma}_g^2} + \frac{\eta^2}{\sigma^2} \\
&= \left(\sum_g \frac{1}{\sigma_g^2} + \frac{1}{\sigma^2}\right)\eta^2 + \sum_g \frac{[\hat{z}_{gt}\sigma_{gt}]^2}{\sigma_g^2} + 2\sum_g \frac{[\hat{z}_{gt}\sigma_{gt}]}{\sigma_g^2} \times \eta \\
&= \underbrace{\frac{1}{\omega^2}\left[\eta^2 + 2\omega^2\eta\sum_g \frac{[\hat{z}_{gt}\sigma_{gt}]}{\sigma_g^2} + \left(\omega^2 \sum_g \frac{[\hat{z}_{gt}\sigma_{gt}]}{\sigma_g^2}\right)^2\right]}_{\text{expanded square in } \eta} - \frac{\omega^4}{\omega^2}\left(\sum_g \frac{[\hat{z}_{gt}\sigma_{gt}]}{\sigma_g^2}\right)^2 + \sum_g \frac{[\hat{z}_{gt}\sigma_{gt}]^2}{\sigma_g^2} \\
&= \underbrace{\frac{1}{\omega^2}\left[\eta + \omega^2\sum_g \frac{[\hat{z}_{gt}\sigma_{gt}]}{\sigma_g^2}\right]^2}_{\text{completed square in } \eta} - \omega^2\left(\sum_g \frac{[\hat{z}_{gt}\sigma_{gt}]}{\sigma_g^2}\right)^2 + \sum_g \frac{[\hat{z}_{gt}\sigma_{gt}]^2}{\sigma_g^2}
\end{aligned}
$$

with the completed square, evaluating the integral $\int_{-\infty}^{\infty} \exp\left(-\frac{1}{2}\left\{\sum_g \left[\frac{\hat{z}_{gt}+\hat{\eta}}{\hat{\sigma}_g}\right]^2 + \frac{\eta^2}{\sigma^2}\right\}\right) d\eta$ leads to

$$
\begin{aligned}
&= \int_{-\infty}^{\infty} \exp\left(-\frac{1}{2}\left\{\frac{1}{\omega^2}\left[\eta + \omega^2\sum_g \frac{[\hat{z}_{gt}\sigma_{gt}]}{\sigma_g^2}\right]^2 - \omega^2\left(\sum_g \frac{[\hat{z}_{gt}\sigma_{gt}]}{\sigma_g^2}\right)^2 + \sum_g \frac{[\hat{z}_{gt}\sigma_{gt}]^2}{\sigma_g^2}\right\}\right) d\eta \\
&= \exp\left[\frac{\omega^2}{2}\left(\sum_g \frac{[\hat{z}_{gt}\sigma_{gt}]}{\sigma_g^2}\right)^2 - \frac{1}{2}\sum_g \frac{[\hat{z}_{gt}\sigma_{gt}]^2}{\sigma_g^2}\right] \times \int_{-\infty}^{\infty} \exp\left(\frac{-1}{2\omega^2}\left[\eta + \omega^2\sum_g \frac{[\hat{z}_{gt}\sigma_{gt}]}{\sigma_g^2}\right]^2\right) d\eta \\
&= \exp\left[\frac{\omega^2}{2}\left(\sum_g \frac{[\hat{z}_{gt}\sigma_{gt}]}{\sigma_g^2}\right)^2 - \frac{1}{2}\sum_g \frac{[\hat{z}_{gt}\sigma_{gt}]^2}{\sigma_g^2}\right] \times \sqrt{2\pi\omega^2}
\end{aligned}
$$

The resulting unconditional likelihood function is in a closed-form expression. After taking logarithm on the equation below and manipulating some algebra, it is identical to the equation in 8

$$
\begin{aligned}
h(\gamma_t) &= \frac{1}{\sqrt{2\pi}\sigma} \times \prod_g \frac{1}{\sqrt{2\pi}\hat{\sigma}_g} \times \sqrt{2\pi\omega^2} \times \exp\left[\frac{\omega^2}{2}\left(\sum_g \frac{[\hat{z}_{gt}\sigma_{gt}]}{\sigma_g^2}\right)^2 - \frac{1}{2}\sum_g \frac{[\hat{z}_{gt}\sigma_{gt}]^2}{\sigma_g^2}\right] \\
&= \left(1 + \sum_g \frac{\sigma^2}{\sigma_g^2}\right)^{-\frac{1}{2}} \times \left(\prod_g \frac{1}{\sqrt{2\pi\hat{\sigma}_g^2}}\right) \times \exp\left[\frac{\omega^2}{2}\left(\sum_g \frac{[\hat{z}_{gt}\sigma_{gt}]}{\sigma_g^2}\right)^2 - \frac{1}{2}\sum_g \frac{[\hat{z}_{gt}\sigma_{gt}]^2}{\sigma_g^2}\right].
\end{aligned}
$$

C Appendix - Numerical Algorithm

In this section, I present a computational strategy to compute and estimate the quantitative model in Section 4. Note that the steps below solve for a competitive equilibrium multiple times.

1. **[Initial values]** Guess occupational prices $\left\{P_o^{\texttt{Guess}}\right\}_o$, final output $Y^{\texttt{Guess}}$, population shares $\left\{\pi_g^{\texttt{Guess}}\right\}_g$, and fraction of workers from group g working in (o,e) pair $\left\{\pi_{o,e|g}^{\texttt{Guess}}\right\}_{o,e|g}$. Discretize the tax progressivity: $\tau^{\texttt{Grid}} = \{0 < \underline{\tau}, \cdots, \overline{\tau} < 1\}$ with the $\texttt{N}_\tau$ grid points.

2. **[Feasible competitive equilibria]** For each grid point $\tau \in \tau^{\texttt{Grid}}$, compute objects of partial and competitive equilibrium up to exogenous policy.

   (a) Given $\left\{P_o^{\texttt{Guess}}\right\}_o$, compute price per efficiency hour units of labor $P_{oeg}\left(\tau^{\texttt{Grid}}\right)$. Based on $P_{oeg}\left(\tau^{\texttt{Grid}}\right)$, compute fraction of workers from demographic group g working in (o,e) pair $\pi_{o,e|g}\left(\tau^{\texttt{Grid}}\right)$ by:

   $$\pi_{o,e|g}\left(\tau^{\texttt{Grid}}\right) = \frac{P_{oeg}\left(\tau^{\texttt{Grid}}\right)}{\sum_{o',e'} P_{o'e'g}\left(\tau^{\texttt{Grid}}\right)}$$

   (b) Given $\left\{\pi_g^{\texttt{Guess}}\right\}_g$, $Y^{\texttt{Guess}}$, and $P_{oeg}\left(\tau^{\texttt{Grid}}\right)$, back out the levels of expected post-tax earnings $\lambda\left(\tau^{\texttt{Grid}}\right)$ from the balanced fiscal budget:

   $$\begin{aligned}\lambda\left(\tau^{\texttt{Grid}}\right) =& 1 + \frac{G\left(Y^{\texttt{Guess}}\right)}{\sum_g \pi_g^{\texttt{Guess}}\left(\tau^{\texttt{Grid}}\right)\Gamma\left(1-\frac{1-\tau^{\texttt{Grid}}}{\theta}\right)\left[\sum_{o',e'} P_{o'e'g}\left(\tau^{\texttt{Grid}}\right)\right]^{\frac{1-\tau^{\texttt{Grid}}}{\theta}}} \\ &- \frac{\sum_g \pi_g^{\texttt{Guess}}\Gamma\left(1-\frac{1}{\theta}\right)\left[\sum_{o',e'} P_{oeg}\left(\tau^{\texttt{Grid}}\right)\right]^{\frac{1}{\theta}}}{\sum_g \pi_g^{\texttt{Guess}}\left(\tau^{\texttt{Grid}}\right)\Gamma\left(1-\frac{1-\tau^{\texttt{Grid}}}{\theta}\right)\left[\sum_{o',e'} P_{o'e'g}\left(\tau^{\texttt{Grid}}\right)\right]^{\frac{1-\tau^{\texttt{Grid}}}{\theta}}}\end{aligned}$$

   (c) Given $\lambda\left(\tau^{\texttt{Grid}}\right)$, compute expected earnings $w_g\left(\tau^{\texttt{Grid}}\right)$ and policy preferences $V_g\left(\tau^{\texttt{Grid}}\right)$. Based on $V_g\left(\tau^{\texttt{Grid}}\right)$, compute fraction of young choosing education $d \in \{\text{Coll,HS}\}$ by:

   $$\pi_{d|g=\{\text{Young}\}\times\text{Gender}}\left(\tau^{\texttt{Grid}}\right) = \frac{\exp\left(V_{d|g=\{\text{Young}\}\times\text{Gender}}\left(\tau^{\texttt{Grid}}\right)\right)}{\sum_{d'}\exp\left(V_{d'|g=\{\text{Young}\}\times\text{Gender}}\left(\tau^{\texttt{Grid}}\right)\right)}$$

   (d) Update worker distribution $\left\{\pi_{o,e|g}^{\texttt{Update}}\left(\tau^{\texttt{Grid}}\right)\right\}_{o,e|g}$ and the relative population shares $\left\{\pi_g^{\texttt{Update}}\left(\tau^{\texttt{Grid}}\right)\right\}_g$ with normalizing the population distribution, i.e., $\sum_g \pi_g^{\texttt{Update}} = 1$.

   (e) Given $\left\{P_o^{\texttt{Guess}}\right\}_o$, $Y^{\texttt{Guess}}$, $\left\{\pi_{o,e|g}^{\texttt{Update}}\left(\tau^{\texttt{Grid}}\right)\right\}_{o,e|g}$, and $\left\{\pi_g^{\texttt{Update}}\left(\tau^{\texttt{Grid}}\right)\right\}_g$, construct occupational goods $Y_o^{\texttt{Demand}}\left(\tau^{\texttt{Grid}}\right)$ and $Y_o^{\texttt{Supply}}\left(\tau^{\texttt{Grid}}\right)$. Compute occupational prices $P_o\left(\tau^{\texttt{Grid}}\right)$ such that $\left\|Y_o^{\texttt{Demand}}\left(\tau^{\texttt{Grid}}\right) - Y_o^{\texttt{Supply}}\left(\tau^{\texttt{Grid}}\right)\right\| < 10^{-20}$.

(f) Given $Y_o^*\left(\tau^{\texttt{Grid}}\right) = Y_o^{\texttt{Demand}}\left(\tau^{\texttt{Grid}}\right) = Y_o^{\texttt{Supply}}\left(\tau^{\texttt{Grid}}\right)$, compute the final output and update $Y^{\texttt{Update}}\left(\tau^{\texttt{Grid}}\right)$ using the final good production function:

$$Y^{\texttt{Update}}\left(\tau^{\texttt{Grid}}\right) = \left[\sum_o Y_o^*\left(\tau^{\texttt{Grid}}\right)^{\frac{\rho-1}{\rho}}\right]^{\frac{\rho}{\rho-1}}$$

(g) Check whether the final good output, population distributions, worker distributions satisfy the convergence condition, each of which constitutes the fixed point and is obtained in the previous iteration:

$$\left\|Y^{\texttt{Guess}} - Y^{\texttt{Update}}\left(\tau^{\texttt{Grid}}\right)\right\| < 10^{-16}$$
$$\left\|\pi_g^{\texttt{Guess}} - \pi_g^{\texttt{Update}}\left(\tau^{\texttt{Grid}}\right)\right\| < 10^{-16}$$
$$\left\|\pi_{o,e|g}^{\texttt{Guess}} - \pi_{o,e|g}^{\texttt{Update}}\left(\tau^{\texttt{Grid}}\right)\right\| < 10^{-16}$$

(h) If not, update the guess, and go back to the step 2a. If so, stop the iteration and denote the set of computed objects $\texttt{CE}\left(\tau^{\texttt{Grid}}\right)$.

3. **[Political general equilibrium]** For $\texttt{CE}\left(\tau^{\texttt{Grid}}\right)$ and $\tau \in \tau^{\texttt{Grid}}$, find the political general equilibrium $\left\{\texttt{CE}\left(\tau^{\texttt{GE}}\right), \tau^{\texttt{GE}}\right\}$ where $\tau^{\texttt{GE}}$ is the general-equilibrium tax progressivity.

   (a) Compute the political process in Proposition 2, i.e., the decision rule of politicians, and find $\tau^{\texttt{GE}}$ that globally maximizes the political process, upon which competitive equilibrium objects $\texttt{CE}\left(\tau^{\texttt{GE}}\right)$ are computed:

$$\tau^{\texttt{GE}} = \texttt{argmax} \sum_g \hat{\omega}_g \psi_g \pi_g^{\texttt{CE}}\left(\tau^{\texttt{Grid}}\right) V_g^{\texttt{CE}}\left(\tau^{\texttt{Grid}}\right)$$