Technological Change and Insuring Job Loss*

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Abstract

We examine the role of technological change in shaping insurance to the unemployed. We integrate technological change, occupation choice, and employment risk into a Bewley-style economy to examine the optimal combination of public insurance transfers and retraining subsidies for unemployed workers. We find that with technological change, the government expands its use of retraining subsidies as part of an optimal policy for unemployed workers.

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Since the dawn of the industrial revolution, there have been recurring fears that the introduction of new technologies will make a share of the workforce obsolete (e.g., Mokyr et al. [2015]). A central question in the face of technological change has been how to adequately provide insurance to workers whose skills and human capital face the risk of becoming obsolete, particularly given the large costs of reallocating workers across occupations and industries (e.g., Kambourov and Manovskii [2009a], Hobijn et al. [2018] and Porzio et al. [2022]).

We revisit the question of how to insure the unemployed in the face of technological change in the context of the United State's experience with technological change in recent decades. A series of influential papers have shown that over the past 50 years the decline in the relative price of equipment and the spread of computers and software in the labor market have played a substantial role in shaping income inequality, the movement of workers across occupations, and earnings losses after displacement (e.g., Krueger [1993], Krusell et al. [2000], Autor et al. [2003], Autor and Dorn [2013], Braxton and Taska [2023]).[1] A common theme of these papers is that the introduction of computers and software have made some workers' skills more valuable, while workers without the skills to use the new technology see the demand for their labor decline. These workers often find new jobs in other occupations, where their skills are still employable, but wages are lower.[2] To revisit this question, we integrate technological change, occupation choice, and employment risk into a Bewley style economy to examine the optimal combination of public insurance transfers and retraining subsidies for unemployed workers. We find that with technological change, the government expands its use of retraining subsidies as part of an optimal policy for unemployed workers.

In this paper, we make two contributions. The first contribution is to embed the quantitative model from Braxton and Taska [2023], which features embodied technological change, occupation choice and employment risk, into a Bewley style economy.[3] In the labor market, workers direct their search for jobs over occupations which differ in their skill requirements, as well as wage piece rates within an occupation. The skill requirements for new jobs in an occupation grow over time due to embodied technological change. Large earnings losses occur following a job separation, when a worker no longer has the necessary human capital to

[1] A related but distinct literature has examined how automation has impacted the labor market and has found that it has played a substantial role in rising inequality and macroeconomic outcomes (e.g., Humlum [2019], Acemoglu and Restrepo [2020], Acemoglu and Restrepo [2022], Moll et al. [2022]). For a recent discussion on this literature see Acemoglu and Restrepo [2019]. Similarly, there is a large literature examining the heterogeneous effects of the transition from agriculture to manufacturing (e.g., Hobijn et al. [2018], Porzio et al. [2022] and references there in).

[2] Recent work has also shown that exposure to technological change is associated with greater income risk. See Violante [2002] for a quantitative model linking technological change to income risk, and Kogan et al. [2020] and Braxton et al. [2021] for empirical evidence.

[3] In Braxton and Taska [2023], we showed that a model with these three features (embodied technological change, occupation choice and employment risk) is consistent with the empirical evidence on the impact of technological change on the outcomes of displaced workers. In Appendix C.2, we show the quantitative model in this paper, which incorporates a retraining decision and self-insurance via savings and borrowing, remains consistent with this empirical evidence.

satisfy the new skill requirements in their prior occupation and must move to a lower paying occupation where their skills are still employable.

The government provides insurance to unemployed workers through public insurance transfers as well as by subsidizing the cost of a retraining program. The model is estimated so that public insurance transfers represent all transfers that unemployed workers receive from the government. We model the retraining program as enrolling in community college classes.[4] To enroll in the retraining program, unemployed workers pay a tuition cost and their human capital increases probabilistically. We calibrate the parameters of the retraining program to match the share of displaced workers who enroll in community college classes as well as their change in earnings as measured by Jacobson et al. [2005a], who link administrative earnings records to community college records for the state of Washington. Finally, agents are also able to partially self-insure through savings and borrowing in an incomplete asset market (e.g., Bewley [1977], Huggett [1993], Aiyagari [1994]).

Our second contribution is quantitative. We perform a policy experiment in which we solve for the optimal combination of public insurance transfers and subsidies to retraining. We evaluate these policies using the welfare of newborn agents. In the model, newborn agents draw their human capital upon entering into the economy. We measure newborn welfare "behind the veil of ignorance," i.e., before an agent draws their human capital. The government finances the public insurance transfer and retraining subsidy using taxes on labor income. The government faces an equity-efficiency trade-off where the benefits of the transfers and retraining subsidies must be weighed against the distortionary effects of raising taxes to finance these programs. We find that the government sets the optimal policy so that it replaces 51% of lost earnings with transfers and subsidizes 19% of the tuition cost of retraining. The optimal policy provides more generous transfers and retraining subsidies relative to the current U.S. policy of replacing 41.2% of lost earnings via transfers and subsidizing 0% of tuition for retraining.[5] On average, an individual would be willing to give up 0.21% of lifetime consumption to transition from an economy with the current policy for unemployed workers to an economy with the optimal combination of public insurance transfers and retraining subsidies.

The optimal policy increases the generosity of transfers to the unemployed relative to current U.S. policy as well as introduces a subsidy for retraining to unemployed workers. The optimal policy includes both public insurance transfers and retraining subsidies because they

[4] We focus on community colleges as the source of retraining as work by McCall et al. [2016], Leung and Pei [2023], and Minaya et al. [2023] has shown that much of the retraining that occurs in the United States occurs through community colleges.

[5] Osikominu [2013] and Kambourov, Manovskii, and Plesca [2012] comment that in the United States since the mid-1990s, programs for displaced workers have focused on job search assistance (i.e., getting individuals reemployed quickly) rather than on teaching new skills through retraining. One exception is Trade Adjustment Assistance (TAA), which offers retraining services for workers who are displaced because of trade. However, a very small fraction of displaced workers are covered by TAA (e.g., Kondo [2018]). See LaLonde [2003] and Barnow and Smith [2015] for detailed histories of retraining in the United States.

each insure consumption at different horizons after job loss. Increasing the generosity of public insurance transfers to the unemployed increases consumption in the immediate aftermath of job loss. Conversely, increasing retraining subsidies increases consumption in the periods after job loss and provides longer-run consumption insurance after job loss. With increased retraining subsidies, more individuals enroll in retraining after job loss. With more individuals enrolling in retraining, this increases the human capital of displaced workers, on average, which raises earnings after job loss through two channels. First, with higher human capital some workers are able to stay in their pre-displacement occupation, which increases their earnings. Second, with higher human capital, workers have higher job finding rates, which increases the likelihood of being employed after job loss and can induce workers to apply for higher paying jobs. With higher earnings after job loss from greater retraining, consumption is higher following job loss.

We show that at the optimal policy the net present value (NPV) of consumption is higher for upwards of 4 years after job loss relative to the baseline economy. Through a decomposition exercise, we find that the increase in consumption in the year of layoff is primarily driven by the increase in transfers. Conversely, starting in the 2nd full year after job loss, the majority of the gains in consumption to the unemployed are attributable to the increase in retraining subsidies. By the 4th year after job loss, all of the increase in consumption relative to the baseline model is coming through the introduction of retraining subsidies. From this decomposition, we conclude that increases in transfers are providing additional consumption insurance in the "short-run" after job loss, while the inclusion of retraining subsidies provide additional "long-run" consumption insurance.

Increasing the generosity of public insurance transfers and retraining subsidies improves consumption smoothing around job loss, which improves equity. However, it comes at the cost of having to raise taxes. Additionally, the increase in public insurance transfers also alters individual's search behavior as unemployed workers search for higher paying but harder to find jobs.[6] This change in search behavior increases the average duration of unemployment as well as the unemployment rate. With a more generous policy towards unemployed workers, and more workers being unemployed, the government has to raise taxes relative to the baseline economy, which reduces efficiency. The government balances the consumption smoothing benefits of increasing the generosity of policies to the unemployed with the efficiency losses of increases taxes at the optimal policy.

Finally, to evaluate the role of technological change in shaping the optimal policy for unemployed workers, we solve for the optimal combination of public insurance transfers and

[6] There is a large literature studying the consumption smoothing benefits of transfers to the unemployed as well as the associated moral hazard costs of changing job search behavior (e.g., Baily [1978], Chetty [2006], and Chetty [2008] among others). We show that our quantitative model is consistent with recent empirical evidence on the change in unemployment duration stemming from increases in transfers to the unemployed, and the model is calibrated to be consistent with consumption declines upon job loss.

retraining subsidies in an environment without technological change. Without technological change, the government sets the optimal policy so that it replaces 61.9% of lost earnings with transfers, and retraining subsidies are set to 8%. Without technological change, unemployment generates a temporary (short-run) decline in both earnings and consumption, which can be partially offset with more generous public insurance transfers. The introduction of technological change creates more persistent (long-run) declines in earnings and consumption for unemployed workers and expands the motive for the government to further subsidize retraining.

Related Literature. This paper contributes to recent work that has examined the optimal policy for unemployed workers in labor search models with incomplete asset markets (e.g., Lentz [2009], Krusell et al. [2010], Koehne and Kuhn [2015], Birinci [2019], Chaumont and Shi [2022], and Braxton et al. [2024]). The novel feature of this paper relative to prior work is considering the mix of the optimal policy between unemployment insurance (transfers) and subsidized retraining programs. Previous work has used quantitative models of the labor market to estimate the welfare (and income) effects of increases in retraining for unemployed workers, where retraining is modeled as a reduction in occupation mismatch (Macaluso [2017]), reducing the cost of switching occupations (Hawkins and Mustre-del Rio [2016]), or removing skill loss while unemployed (Jung and Kuhn [2012]).[7] This paper adds to the literature by using micro-estimates of the impact of retraining through community colleges to discipline the impact of retraining in an equilibrium model of the labor market, and solving for the optimal subsidy to retraining programs in conjunction with public insurance transfers received by the unemployed.[8]

Additionally, our paper is related to the literature that has examined how technological progress can be associated with skill loss and/or decreases in demand for certain groups of workers. Katz and Margo [2014] provide a detailed history of technological change in the U.S. over the past 150 years and its implications for workers across the skill distribution. Late 19th century technological change was characterized by “de-skilling," which entailed more skilled workers being replaced by machines and less skilled workers to operate them (e.g., Atack et al. [2024] and references there-in). Work by Hobijn et al. [2018] and Porzio et al. [2022] have shown that structural transformation from agriculture to manufacturing in the early 20th century primarily occurred via new cohorts of workers. Relative to these earlier time periods, the more recent period of technological change that we examine entails “skill-biased" technological change where the introduction of new technologies often complements skilled workers (e.g., Krusell et al. [2000]). In quantitative models, work by Violante [2002], Restrepo [2015], and

[7] Spinnewijn [2013] characterizes the optimal path of training and unemployment insurance over an unemployment spell using a Hopenhayn and Nicolini [1997] style framework.

[8] An extensive empirical literature has examined the effects of training programs on the outcomes of participants. For a recent survey of the effects of retraining programs, see Card et al. [2018].

Adão et al. [2024] have shown that this form of (skill-biased) technological progress and skill loss has important implications for inequality, unemployment dynamics as well as welfare.[9] We contribute to this literature by highlighting how retraining subsidies, in conjunction with transfers to the unemployed, is part of an optimal policy in the face of technological change.

Finally, a recent literature has examined the policy response to increases in automation and exposure to AI. While several papers consider how the tax and transfers system should respond to greater automation and use of AI (e.g., Guerreiro et al. [2022], Costinot and Werning [2023], Beraja and Zorzi [2024] and Schaefer and Schneider [2024])), work by Jaimovich et al. [2021] shows the potential for welfare gains from increased retaining. Relative to Jaimovich et al. [2021], we solve for the optimal combination of subsides for retraining and public insurance transfers.[10]

The remainder of this paper is structured as follows. Section 1 presents motivating graphical evidence on the link between technological change and greater scarring of earnings after job loss. In Section 2, we present a quantitative model that is consistent with the empirical motivating evidence that can be used to examine the optimal combination of transfers to the unemployed and subsidies for retraining. In Section 3, we discuss the calibration of the quantitative model. Section 4 presents the optimal policy results, and finally Section 5 concludes.

1 Motivating Empirical Evidence

In this section, we present graphical evidence on the link between exposure to technological change and the size of earnings losses among displaced workers based upon our earlier work in Braxton and Taska [2023], hereafter referred to at BT.

Data. In BT, we use data on detailed skill requirements from online vacancies provided by Burning Glass Technologies (hereafter Burning Glass) to measure exposure to technological change by occupation. Burning Glass identifies newly posted online vacancies and records the skills listed in the vacancy. Using these skill requirements, we measure the share of vacancies listing a computer or software requirements by occupation (4-digit SOC code) and year. We use the change in the share of vacancies listing a computer or software requirement over time by occupation as our measure of exposure to technological change.

[9] Additionally, in a recent paper Wolcott [2021] shows how changing demand for workers across the skill distribution due to technological change has impacted aggregate trends in employment.

[10] Additionally, while automation involves replacing workers with new technologies, the focus of this paper, technological change, involves the introduction of new technologies that enhance worker productivity, provided the worker possesses the necessary skills to utilize them. This distinction is similar to notation of labor-augmenting and labor-automation innovations in Autor et al. [2024]. See also Kogan et al. [2023] for a discussion on new technologies that complement versus substitute for labor.

We then measure the outcomes of displaced workers using the CPS Displaced Worker Supplement (DWS). The DWS records the occupation and earnings before and after layoff for workers who report that they have been displaced within the past three years. Workers are defined to be *displaced* if they lost their job due to: (1) their company or plant shutting down, (2) their shift or position being eliminated, or (3) insufficient work. These reasons are designed to identify workers who have been laid-off for reasons that are exogenous to their characteristics. We focus on a sample of displaced workers who are: (1) between the ages of 25 and 65, (2) were displaced between 2010 and 2017, and (3) were employed at the time of the DWS and prior to displacement.[11] See BT for additional details on the data, as well as additional robustness exercises on the graphical evidence presented below.

Graphical Evidence. We begin by showing that there has been substantial heterogeneity in the change in computer and software requirements across occupations. To observe this heterogeneity, we place displaced workers into quintiles based on the change in the share of vacancies that listed a computer or software requirement between 2010 and 2017 in the occupation from which they were displaced. Panel (a) of Figure 1 presents the average change in computer and software requirements by quintile. The figure shows that workers in the bottom quintile lost their job in occupations that were experiencing a decline in computer and software requirements between 2010 and 2017. Individuals in the second quintile lost their job in occupations that on average had a modest increase in computer and software requirements. Conversely, individuals in the top three quintiles lost their job in occupations that experienced an increase in computer and software requirements. For example, workers in the fifth quintile lost their job in occupations where the share of vacancies listing a computer and software requirement increased by nearly 10 percentage points. This heterogeneity allows us to estimate how the outcomes of displaced workers are affected by changes in computer and software requirements in the occupations from which they were displaced, which we turn to next.

We find that individuals displaced from occupations undergoing a larger increase in computer and software requirements experience a larger decline in earnings. Panel (b) of Figure 1 shows the average change in earnings following displacement by quintile of the change in computer and software requirements for the occupation from which an individual was displaced. The figure shows that individuals displaced from an occupation in the first quintile (occupations that experienced a decline in computer and software requirements) experienced relatively small declines in earnings of approximately 3% of pre-displacement earnings. Conversely, individuals in the fifth quintile, who were displaced from occupations undergoing the largest increases in computer and software requirements, have nearly a 14% decline in earnings. This

[11] We additionally require that individuals have non topcoded earnings both before and after displacement, and make more than \$100 weekly in 2012 (CPI) dollars both before and after displacement. We impose the minimum earnings criteria as some workers report being employed with zero earnings.

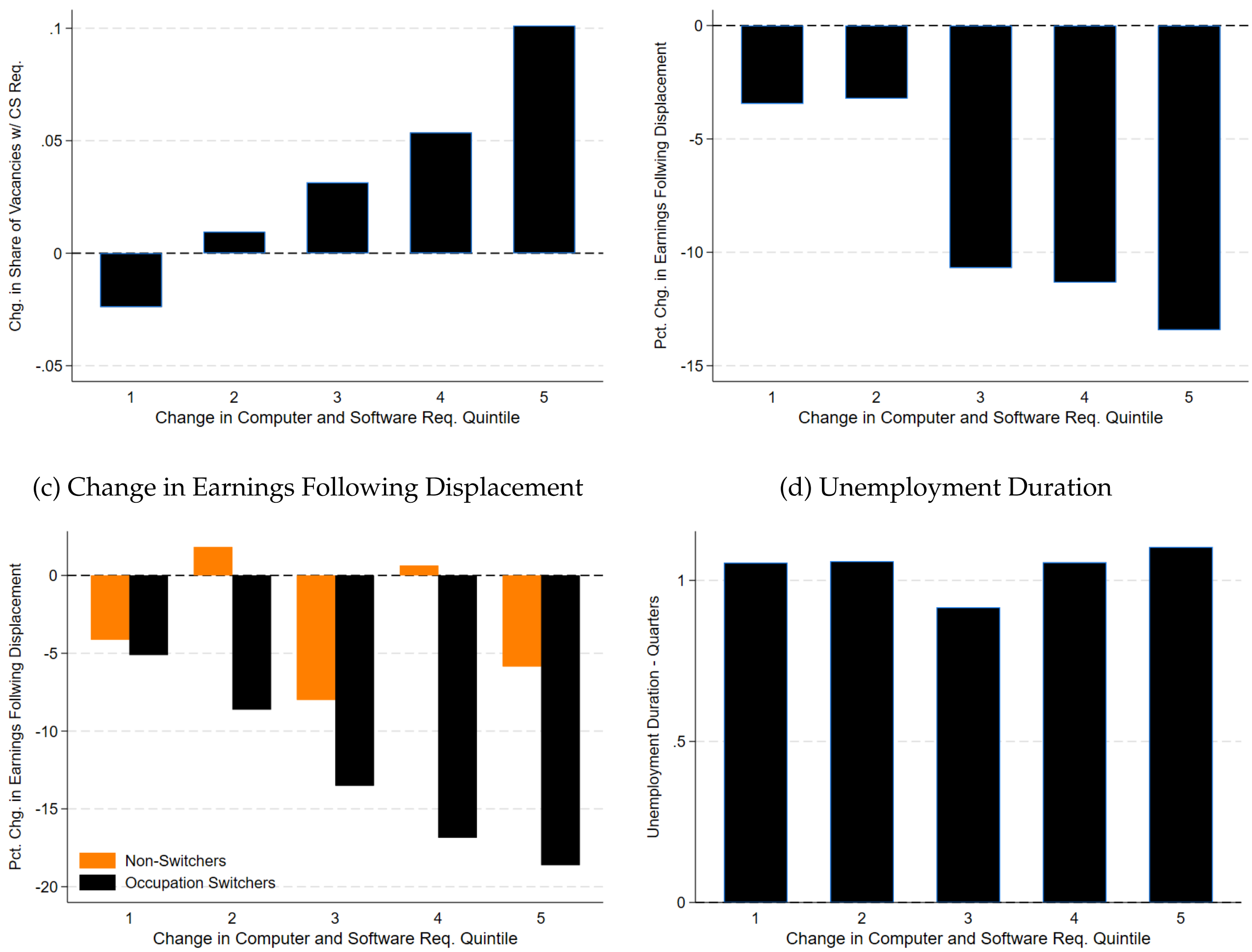
Figure 1: Change in Computer & Software Req. and Displaced Worker Outcomes

(a) Changes in Computer & Software Requirements

(b) Change in Earnings Following Displacement

(c) Change in Earnings Following Displacement

(d) Unemployment Duration



Notes: Panel (a) shows the average change in computer and software requirements by quintile of changes in computer and software requirements. Panel (b) shows the average change in earnings for displaced workers by quintile of change in computer and software requirements. Panel (c) shows the average change in earning by quintile for occupation switchers (black bars) and non-switchers (orange bars). Panel (d) shows the average unemployment duration by quintile. Individuals are placed into quintiles based on the occupation from which they were displaced. Occupations are defined using four-digit SOC codes.

observation suggests that changes in computer and software requirements play a role in explaining the earnings losses of displaced workers. We next examine the mechanisms through which changes in computer and software requirements affect the outcomes of displaced workers.

We find that changes in computer and software requirements affect earnings following displacement through occupation switching. Panel (c) of Figure 1 presents the average change in earnings following displacement for individuals who switch occupations (black bars) and individuals who do not switch occupations (orange bars) by quintile of the change in computer and software requirements. The figure shows that for individuals in the first quintile, the change in earnings following job loss is small and the outcomes of occupation switchers and stayers are nearly identical. Conversely, for individuals in the top three quintiles, there are large declines in earnings, and the decline in earnings is largely driven by occupation switchers. For instance, among individuals in the fifth quintile, occupation switchers experience, on average, nearly a 18% decline in earnings, while non-switchers experience just over a 5% decline in earnings.

The individuals who switch occupations after job loss may be doing so because they no longer have the skills to work in their prior occupation. To test this hypothesis, we examine the nature of occupation switching and show in Appendix A that individuals displaced from an occupation experiencing a larger increase in computer and software requirements are more likely to move to an occupation with lower computer and software requirements (relative to their original occupation).

Finally, one may wonder if the result that workers who are more exposed to increasing computer and software requirements suffer larger earnings losses because of mechanisms related to the search process. For example, if these workers spend longer in unemployment they may incur larger earnings losses due to mechanisms related to duration dependence. In panel (d) of Figure 1, we show the average unemployment duration for workers in each quintile. We find a relatively flat profile of unemployment duration as a function of the change in computer and software requirements in an individual's pre-displacement occupation. In particular, workers in the first quintile on average have an unemployment duration of 1.06 quarters, while for workers in the fifth quintile their average duration is 1.1 quarters. We view this result as evidence against the notion that our results are driven by mechanisms related to search and/or duration dependence style arguments.

The results presented in Figure 1 demonstrate that the decline in earnings following job loss occurs largely among individuals displaced from occupations undergoing an increase in computer and software requirements. Further, this decline in earnings is concentrated among individuals who switch occupations following job loss. We additionally find that individuals displaced from an occupation undergoing a larger increase in computer and software requirements are more likely to move to an occupation with lower computer and software requirements. We view these results as consistent with the notion that the decline in earnings following job loss is driven by technological change, which requires workers to have new skills to perform newly created jobs in their prior occupation. Displaced workers who do not have the new skills that have become required in their prior occupation search for a job in another occupation where their skills are still employable, but they are paid a lower wage. This suggests that retraining may play a role as part of optimal policy for unemployed workers. In the next section, we formulate a quantitative model of the labor market that is consistent with these empirical patterns and allows for examining the role of retraining in optimal policy for the unemployed.

2 Model

In this section, we develop the quantitative model that we will use to compute optimal transfers and retraining subsidies to the unemployed. The model builds from the model of directed search with embodied technological change in Braxton and Taska [2023] and incorporates incomplete markets in the tradition of Bewley [1977], Huggett [1993], and Aiyagari [1994]. Additionally, the model includes a retraining choice for unemployed workers, where the cost of retraining can be subsidized by the government.

Time is discrete and runs forever. There is a unit measure of workers and a continuum of potential entrant firms. There are T overlapping generations of risk averse individuals, who each live for T periods. At the start of each period, individuals direct their search for jobs which differ in their wage and occupation. Individuals then participate in an asset market where they make a consumption-savings decision. Unemployed workers also make a decision on whether or not to retrain. We next provide details on the structure of the economy and in Section 2.1 present the Bellman equations that govern the model economy.

Occupations and Technological Change. In the labor market, there are $K \geq 2$ occupations, which differ in the level of technology used in production. Let z_j denote the level of technology at time j, which grows at a constant rate $g \geq 0$. Let $c_k \in [0, 1]$ denote the technology intensity of an occupation $k \in \mathcal{K}$. At time j, all vacancies posted in occupation k use technology level $z_{k,j} = c_k z_j$.

Potential entrant firms pay an entry cost $\kappa_j(k)$ to post a vacancy at time j in occupation $k \in \mathcal{K}$, and choose which occupation k to post a vacancy in as well as the wage piece rate for the job, subject to a free-entry condition. Workers direct their search across occupations and wage piece rates, and vacancies that go unfilled exit the market. Once a match is formed, the level of technology in the match is fixed for the duration of the match.[12] For an individual to

[12] This form of technological change is embodied in matches (e.g., Mortensen and Pissarides [1998], Violante [2002], Postel-Vinay [2002], and Eyigungor [2010]). With embodied technological change a worker will always be qualified for their current job. As we discussed in Braxton and Taska [2023], we use a model of embodied

become employed with a newer vintage of technology, they must match with a new vacancy either through on-the-job search or after a spell of unemployment.

Heterogeneity. Individuals in the model economy are heterogeneous along several dimensions. Individuals are either employed ($e = W$) or unemployed ($e = U$) and search in the labor market both while employed and unemployed. Search is directed across jobs that differ by occupation $k \in \mathcal{K}$ and wage piece rate $\omega \in [0, 1]$, which specify the share of per-period output that the worker receives as a wage.[13]

Additionally, individuals are heterogeneous in their general human capital as well as occupation specific human capital, which we refer to as "experience." General human capital is denoted by $h \in \mathcal{H} \equiv [\underline{h}, \bar{h}]$. As in Kambourov and Manovskii [2009b], workers are either inexperienced ($x = N$) or experienced ($x = E$) in their current occupation k. Workers become experienced with probability λ_E when they remain employed in an occupation k. Becoming experienced raises a worker's production and wages in an occupation by a factor $A_E > 1$. Experienced workers become inexperienced by accepting a job in a new occupation, or when they are unemployed they become an inexperienced worker with probability λ_N.

Individuals are risk averse and discount the future at rate $\beta \in (0, 1)$. Agents have access to an asset market where they are able to save at the risk-free rate r, or borrow at an interest rate r_b > r. Let $a \in \mathcal{A} \equiv [\underline{A}, \bar{A}]$ denote the net asset position of an individual.[14] New workers enter as inexperienced unemployed workers, with zero assets, and draw their (general) human capital from a distribution $\Gamma_j(h) : \mathcal{H} \to [0, 1]$.

Labor Market Matching and Production. Workers direct their search for jobs across occupations and wage piece rates both while employed and unemployed. Let $M(s, v)$ denote the labor market matching function, and define labor market tightness to be the ratio of vacancies (v) to searching workers (s).[15] Because search in the labor market is directed, there is a separate labor market tightness for each submarket, where submarkets are defined by the time period j, occupation k, as well as the wage piece rate (ω), worker's age (t), human capital (h), experience (x), and assets (a).[16] In each submarket the job finding rate for individuals, $p(\cdot)$, is a function

technological change so that technological change does not cause job loss to be consistent with the empirical evidence presented in Braxton and Taska [2023].

[13]Similar to Kaplan and Menzio [2016], we model wages using piece rates for tractability with search and assets.

[14]We assume that agents face the natural borrowing limit. In an earlier version of this paper, we assumed that agents can only save in the asset market and found similar results. In the quantitative model, we set $\bar{A}$ so that agents never reach $\bar{A}$ in equilibrium.

[15]Searching workers include both employed and unemployed individuals and we assume that employed workers have the same search efficiency as unemployed workers.

[16]As in Chaumont and Shi [2022], the firm conditions on the worker's assets since the worker's asset position influences their on-the-job search decision and hence the probability that the worker separates from the firm.

of labor market tightness $\theta^x_{j,t}(h,a,k,\omega)$, such that $p(\theta^x_{j,t}(h,a,k,\omega)) = \frac{M(s^x_{j,t}(h,a,k,\omega),v^x_{j,t}(h,a,k,\omega))}{s^x_{j,t}(h,a,k,\omega)}$. The hiring rate for firms $p_f(\cdot)$ is also a function of labor market tightness and is given by $p_f(\theta^x_{j,t}(h,a,k,\omega)) = \frac{M(s^x_{j,t}(h,a,k,\omega),v^x_{j,t}(h,a,k,\omega))}{v^x_{j,t}(h,a,k,\omega)}$. The worker and the firm separate each period exogeneously with probability δ. When a worker is hit by the separation shock (δ) they are able to search for another job immediately with probability λ_S.

When workers with human capital h and experience x match with a firm in occupation k at time j, they produce $f(c_k z_j, h, x)$. As we discuss in more detail in Section 3, we use an "up-to-the-task" production function which requires that workers have a minimum amount of human capital to produce with a given level of technology. With embodied technological change, the minimum amount of human capital to match with new vacancies in an occupation will increase over time.

Unemployment Insurance and Retraining. Unemployed individuals receive a public insurance transfer $b_j > 0$ from the government at time j. Public insurance transfers incorporate all forms of assistance that unemployed workers receive, such as unemployment insurance benefits, emergency unemployment assistance, and general transfer programs such as welfare and food stamps. In the model, public insurance transfers are funded through a proportional labor income tax τ that is levied on all employed workers. Additionally, unemployed workers have access to home production $d_j > 0$. As we discuss in Section 3, we will calibrate the value of home production to match consumption upon job loss. Thus, one can think of home production encapsulating other means that unemployed workers have to smooth consumption such as changes in spousal labor supply (e.g., Blundell et al. [2016]), moving back to ones parent's house (e.g., Kaplan [2012]) or direct transfers from friends and family.

Unemployed workers also have access to a retraining program. To enter the retraining program, workers pays a cost $(1-s)\kappa_{R,j}$, where $\kappa_{R,j}$ is the tuition cost in period j and $s \in [0,1]$ is the share of the tuition cost subsidized by the government. After entering the retraining program, an unemployed worker's general human capital (h) increases with probability λ_R. Enrolled individuals also incur a utility cost $\psi > 0$, which can be interpreted as lost leisure due to time spent in the retraining program.[17] Enrolling in the retraining program also imposes a cost $\zeta\kappa_{R,j}$ on the government, which is also funded through the proportional labor income tax.[18]

[17] In the literature that examines college enrollment (e.g., Abbott et al. [2019], Luo and Mongey [2019], and Hendricks et al. [2021] among others) utility costs of enrollment are often needed to get the share of students entering college to align with the data.

[18] We model the retraining program as incurring a cost to the government since we will calibrate the model to estimates of the impact of community college classes on the outcomes of displaced workers. Kane and Rouse [1999] find that the costs of community colleges are largely paid by the government rather than via the tuition of enrolled students.

Stationarity. In equilibrium, the cost of posting a vacancy $\kappa_j(k)$, the tuition cost of retraining $\kappa_{R,j}$, the value of public insurance transfers b_j, home production d_j, and the distribution of human capital of new workers $\Gamma_j(h)$ must grow at the rate of technological progress g for the economy to be stationary. It is convenient to analyze a transformed economy where the cost of posting a vacancy, the cost of retraining, the value of public insurance, and the distribution of human capital for new workers are constant over time. In the transformed economy, the latest vintage of technology is held fixed and is denoted by $\bar{z}$. The level of technology in a match (z) and workers' general human capital (h) evolve relative to the latest vintage of technology, which requires that they depreciate at rate $\mu = \frac{1}{1+g}$. In the estimation, we model the depreciation of match technology (z) and human capital (h) as occurring stochastistically so that they depreciate by factor μ, on average, over a model year.

Timing and Aggregate State. The timing of the period is such that at the start of the period, shocks to human capital, match technology, job destruction, and experience are realized. After the shocks are realized, agents then search for jobs in the labor market. After the labor market closes, agents make their consumption, savings, as well as retraining decisions and the model period ends.

The aggregate state of the economy is given by $\Omega(e, t, h, x, k, \omega, z, a) \rightarrow [0, 1]$, which is a distribution of workers across employment status (e), ages (t), general human capital (h), experience (x), occupations (k), wage piece rates (ω), vintages of technology (z), and assets (a). We prove in Appendix B.4 that the model is conditionally Block Recursive (e.g., Menzio and Shi [2011]) and that the aggregate state does not affect the behavior of agents in the economy.[19] For presentation purposes, in the next section where we present the Bellman equations that govern the behavior of agents in the economy, we exclude the aggregate state.

2.1 Bellman Equations

This section presents the Bellman equations that govern the behavior of workers and firms in equilibrium. In the Bellman equations below, we present an agent's problem after the labor market has closed for the period.

Unemployed Workers. Let $U_t^N(h, a, 0)$ denote the value of being an inexperienced, unemployed worker of age t, with assets a, and human capital h. In the current period, the agent makes their consumption-savings decision as well as a decision on whether or not to retrain. If the worker chooses to retrain ($R = 1$), then they pay $(1 - s)\kappa_R$, where κ_R is the tuition cost of retraining and s is the share of tuition that is subsidized by the government. Additionally enrolling in the retraining program generates a utility cost ψ. For individuals who enroll in

[19] As we discuss in greater detail in Section 2.2, the model is Block Recursive conditional on a given tax rate τ.

the retraining program, at the start of the next period their human capital increases with probability λ_R. Unemployed workers receive public insurance transfers b, which are provided by the government and funded through taxes on employed workers. Finally, unemployed workers also receive the value of home production d, which proxies for other resources that the unemployed have available.

At the start of the next period, shocks to human capital are realized (which depend upon the retraining choice) and unemployed workers enters the labor market. In the labor market, an inexperienced unemployed worker searches across the set of occupations as well as wage piece rates for inexperienced workers and applies for a job with the highest continuation value. The value to an inexperienced unemployed worker is,

$$U_t^N(h,a,0) = \max_{a' \geq \underline{A}, R \in \{0,1\}} u(c) - R\psi + \beta \mathbb{E}\left[\hat{U}_{t+1}^N(h',a',0)\right] \quad \forall t \leq T$$

$$U_{T+1}^N(h,a,0) = 0,$$

where $\hat{U}_{t+1}^N(h',a',0)$ denotes the expected value of search for an inexperienced, unemployed worker, which is given by,

$$\begin{aligned}\hat{U}_{t+1}^N(h',a',0) = \max_{(k,\omega)\in\mathcal{K}\times[0,1]} & \; p(\theta_{t+1}^N(h',a',k,\omega))W_{t+1}^N(h',a',\bar{z},k,\omega) \\ & + \left(1 - p(\theta_{t+1}^N(h',a',k,\omega))\right) U_{t+1}^N(h',a',0),\end{aligned}$$

subject to the budget constraint,

$$c + q(a')a' + R(1-s)\kappa_R \leq b + a + d,$$

where the bond price $q(a')$ is a function of an individual's asset choice, such that

$$q(a') = \mathbb{I}\{a' < 0\}\frac{1}{1+r_b} + \mathbb{I}\{a' \geq 0\}\frac{1}{1+r} \tag{1}$$

and the law of motion for a worker's human capital, which is indexed by employment status U and their retraining decision $R \in \{0,1\}$,

$$h' = H(h,U,R).$$

Experienced, unemployed workers face a problem similar to that of inexperienced, unemployed workers. The main difference is that experienced, unemployed workers search in the experienced labor market for a job in their own occupation and in the inexperienced market for jobs in all other occupations. Appendix B.1 contains the Bellman equation for experienced, unemployed workers.

Employed Workers. Let $W_t^N(h,a,z,k,\omega)$ denote the value of an age t inexperienced worker with human capital h and assets a, who is employed at a firm in occupation k that uses technology $z \leq \bar{z}$, and receives share ω of the match output as a wage. In the current period, the agent makes their consumption and savings choice, and receives utility from consumption.

At the start of the next period, shocks to human capital and match technology are realized, and the worker separates from their match with probability δ. For workers who are hit by the separation shock, with probability λ_S they are immediately able to search for another job. If the worker is not hit by the separation shock, then the worker becomes experienced in occupation k with probability λ_E. After the experience shock is revealed, the worker engages in on-the-job search where they search over occupations and wage piece-rates. If the worker becomes experienced, then they can search for a job in their own occupation in the experienced labor market or search for a job in all other occupations in the inexperienced labor market. If the worker does not become experienced, then they search in the inexperienced labor market for all occupations. The continuation value of an inexperienced, employed worker is,

$$\begin{aligned} W_t^N(h,a,z,k,\omega) = \max_{a' \geq \underline{A}} u(c) + \beta \mathbb{E} \Big[\delta \Big(\lambda_S \hat{U}_{t+1}^N(h',a',0) + (1-\lambda_S) U_{t+1}^N(h',a',0) \Big) \\ + (1-\delta) \Big(\lambda_E \hat{W}_{k,t+1}^E(h',a',z',k,\omega) + (1-\lambda_E) \hat{W}_{t+1}^N(h',a',z',k,\omega) \Big) \Big] \quad \forall t \leq T \end{aligned}$$

$$W_{T+1}^N(h,a,z,k,\omega) = 0,$$

where $\hat{W}_{t+1}^N(h',a',z',k,\omega)$ denotes the value of on-the-job search for an inexperienced employed worker from occupation k with wage piece-rate ω, and is given by,

$$\begin{aligned} \hat{W}_{t+1}^N(h',a',z',k,\omega) = \max_{(\tilde{k},\tilde{\omega}) \in \mathcal{K} \times [0,1]} & p(\theta_{t+1}^N(h',a',\tilde{k},\tilde{\omega})) W_{t+1}^N(h',a',\bar{z},\tilde{k},\tilde{\omega}) \\ & + \Big(1 - p(\theta_{t+1}^N(h',a',\tilde{k},\tilde{\omega}))\Big) W_{t+1}^N(h',a',z',k,\omega), \end{aligned}$$

and $\hat{W}_{t+1}^E(h',a',z',k,\omega)$ denotes the value of on-the-job search for a worker who is experienced in occupation k with wage piece-rate ω, and is given by,

$$\begin{aligned} \hat{W}_{t+1}^E(h',a',z',k,\omega) = \max \Big\{ & \max_{\tilde{\omega} \in [0,1]} p(\theta_{t+1}^E(h',a',k,\tilde{\omega})) W_{t+1}^E(h',a',\bar{z},k,\tilde{\omega}) + \Big(1 - p(\theta_{t+1}^E(h',a',k,\tilde{\omega}))\Big) W_{t+1}^E(h',a',z',k,\omega); \\ & \max_{(\tilde{k},\tilde{\omega}) \in \mathcal{K}/\{k\} \times [0,1]} p(\theta_{t+1}^N(h',a',\tilde{k},\tilde{\omega})) W_{t+1}^N(h',a',\bar{z},\tilde{k},\tilde{\omega}) + \Big(1 - p(\theta_{t+1}^N(h',a',\tilde{k},\tilde{\omega}))\Big) W_{k,t+1}^E(h',a',z',k,\omega) \Big\}, \end{aligned}$$

subject to the budget constraint,

$$c + q(a^{'})a^{'} \leq (1-\tau)\omega f(c_k z, h, N) + a,$$

the bond price in equation 1, and the laws of motion for worker's human capital, and the firm's technology,

$$h^{'} = H(h, W), \quad z^{'} = Z(z).$$

Experienced, employed workers face a problem similar to that of inexperienced employed workers. Appendix B.2 contains the Bellman equations for experienced employed workers.

Firms. Let $J_t^N(h, a, z, k, \omega)$ denote the value to a firm in occupation k of being matched with an age t inexperienced worker with human capital h, assets a, wage piece rate ω, and using technology $z \leq \bar{z}$. In the current period, the firm produces and makes wage payments to the worker. At the start of the period, shocks to the worker's human capital and technology within the match are realized, and with probability δ the match ends exogenously. If the match avoids the separation shock, then the worker becomes experienced with probability λ_E and searches in the labor market.

If the worker does not match with another job via on-the-job search, then the match continues and the firm continues to receive the benefits of the match. The probability that the worker leaves the firm via on-the-job search depends on their asset choice in the current period as well as where the worker searches for a new match in the next period. Let $y = (t, h, a, z, x, k, \omega)$ denote the state of the individual that the firm is matched with in the current period, and let $a^{'}(y)$ denote the agent's asset choice. Let $y^{'} = (t+1, h^{'}, a^{'}(y), z^{'}, x^{'}, k, \omega)$ denote the agent's state in the next period when making their decision about which occupation and wage piece rate to search for a job in (i.e., after shocks to human capital, match technology, and experience are realized). Let $\hat{k}(y^{'})$ denote the occupation where the worker searches for a job, and let $\hat{\omega}(y^{'})$ denote the wage piece-rate where the worker searches for a job. With probability $p(\theta_{t+1}^{x(\hat{k})}(h^{'}, a^{'}(y), \hat{k}(y^{'}), \hat{\omega}(y^{'})))$ the worker matches with another job via on-the-job search.[20] The

[20]Note that when the worker becomes experienced, their occupation search choice determines whether they search in the experienced market (i.e., if they choose to search in their current occupation k) or the inexperienced market (i.e., if they choose to search in any other occupation $\tilde{k} \in \mathcal{K}/\{k\}$). For this reason, we denote the market the agent searches in as $x(\hat{k})$.

value to the firm is given by,

$$
\begin{aligned}
J_t^N(h,a,z,k,\omega) &= (1-\omega)f(c_k z,h,N) \\
&+ \frac{1-\delta}{1+r}\mathbb{E}\left[(1-\lambda_E)\left(1-p(\theta_{t+1}^N(h',a'(y),\hat{k}(y'),\hat{\omega}(y')))\right)J_{t+1}^N(h',a'(y),z',k,\omega)\right] \\
&+ \frac{1-\delta}{1+r}\mathbb{E}\left[\lambda_E\left(1-p(\theta_{t+1}^{x(\hat{k})}(h',a'(y),\hat{k}(y'),\hat{\omega}(y')))\right)J_{t+1}^E(h',a'(y),z',k,\omega)\right] \quad \forall t \leq T
\end{aligned}
$$

$J_{T+1}^N(h,a,z,k,\omega) = 0,$

and the laws of motion for worker's human capital and the firm's technology,

$$h' = H(h,W), \quad z' = Z(z).$$

Firms matched with experienced workers face a similar problem as firms matched with inexperienced workers. Appendix B.3 contains the Bellman equations for a firm matched with an experienced worker.

Firms must pay cost $\kappa(k)$ to post a vacancy. As search is directed, a vacancy specifies a wage piece rate ω and occupation k as well as the age t, experience $x \in \{E,N\}$, human capital h, and assets a for the worker. Free-entry requires that

$$\kappa(k) \geq p_f(\theta_t^x(h,a,k,\omega))J_t^x(h,a,\bar{z},k,\omega) \ \text{ for } x \in \{E,N\}, \tag{2}$$

where $p_f(\theta_t^x(h,a,k,\omega))$ is the matching rate for firms in occupation k paying wage piece rate ω with an age t worker with skills h, assets a, and experience $x \in \{E,N\}$. The free-entry condition binds for all submarkets such that $\theta_t^x(h,a,k,\omega) > 0$.

Government. The government provides public insurance transfers to unemployed workers and can subsidize the tuition cost of the retraining program. We assume the government must maintain a balanced budget in every period.

All unemployed individuals receive a public insurance transfer b. A fraction $R_t(h) \in [0,1]$ of age t unemployed individuals with human capital h enroll in the retraining program. Each individual that enrolls in the retraining program generates a cost to the government of $\zeta\kappa_R + s\kappa_R$, which represents the cost of running the program (ζ) and subsidies to unemployed workers who enroll (s). Public insurance transfers and the retraining program are paid for by a proportional labor income tax, τ, which is levied on all employed individuals to satisfy,

$$\sum_{(h,t)} u_t(h)\left[b + R_t(h)(\zeta\kappa_R + s\kappa_R)\right] = \sum_{(t,h,z,x,k,\omega)} \tau\omega f(c_k z,h,x)e_{k,\omega,t}^x(h,z), \tag{3}$$

where $u_t(h)$ is the mass of individuals with human capital h that are unemployed at age t, and $e^x_{k,\omega,t}(h,z)$ is the mass of age t agents with skill h and experience x that are employed at the firm with technology z in occupation k at wage rate ω.

2.2 Equilibrium

A recursive competitive equilibrium for this economy is a list of household policy functions for assets $\{a'_{e,x,t}(h,a,z,k,\omega)\}$, occupations as well as wages (piece rates) to search for employment in $\{\hat{k}^x_{e,t}(h,a,z,k,\omega)\}$ and $\{\hat{\omega}^x_{e,t}(h,a,z,k,\omega)\}$, and retraining decisions $\hat{R}^x_t(h,a,k)$, a labor market tightness function $\{\theta^x_t(h,a,k,\omega)\}$, a tax rate τ, and a distribution of individuals across states $\Omega(e,t,h,x,k,\omega,z,a) \to [0,1]$ such that

1. Given prices, the households' policy functions solve their respective dynamic programming problems.

2. The labor market tightness in each occupation is consistent with the free-entry condition in equation 2.

3. The tax rate τ balances the government's budget constraint (equation 3).

4. The distribution of individuals across states Ω is consistent with individual policy functions.

In Appendix B.4, we prove that if the government's budget constraint is ignored and the tax rate τ is taken as given, then the model is conditionally Block Recursive (e.g., Menzio and Shi [2011]). Given an exogenous tax rate, the Block Recursive nature of the model means that the individual and firm problems can be solved independent of the distribution of workers across states. In practice, we iterate on the tax rate to solve the model.

3 Calibration

In this section, we discuss the calibration of the quantitative model.[21] Where possible we estimate our steady state to match moments from 2010 to 2017 to align with the timing of the empirical evidence in Section 1. While the calibration of our model is performed jointly, we discuss the moments that are most informative for each model parameter. In Section 3.1 we present a series of non-targeted moments that serve as a model validation exercise.

[21] In Appendix B.5, we present the algorithm for solving the model.

Preferences and Demographics. The model is estimated at a quarterly frequency. A worker's life span is set to $T = 120$ quarters (30 years). Newly born agents enter the model as unemployed, inexperienced workers with zero assets. Newly born agents draw their initial human capital from an inverted exponential distribution with parameter λ_H, which is calibrated to match the difference in the 75th and 25th percentile log earnings residuals among individuals with less than 5 years of potential experience from a regression of log earnings on experience.[22] We estimate this difference to be 0.38 using data from the CPS Outgoing Rotation Groups (CPS-ORG).[23]

The agent's preferences over non-durable consumption are given by,

$$u(c) = \frac{c^{1-\sigma} - 1}{1 - \sigma}.$$

We set the risk aversion parameter to a standard value, $\sigma = 2$. The discount factor of workers β is calibrated to hit the 75th percentile of the net liquid asset to income (NLATI) ratio. We measure the 75th percentile of the NLATI ratio to be 21.2% using data from the 2010 and 2013 waves of the SCF.[24] We set the annualized risk-free rate r to 4%, and we set the interest rate on borrowing r_b to 13.06%, which is the average real interest rate for borrowing on credit cards in the 2010 and 2013 waves of the SCF.

Technological Change. We use the increase in the share of vacancies listing computer or software requirements to set the growth rate of technology g. Braxton and Taska [2023] find that the share of vacancies listing computer or software requirements grew by 1.5% per annum between 2010 and 2017. We normalize the value of the frontier technology to 1 (i.e., $\bar{z} = 1$) and then assign a grid of values for technology $z \in \mathcal{Z}$ where the grid points are spaced so that moving up one grid point is consistent with a growth rate of $g = 1.5\%$. All matches between workers and firms start at the frontier technology $\bar{z}$ and then evolve according to the following stochastic process,

$$Z(z) = z' = \begin{cases} z\mu & \text{w/ pr. } \iota \\ z & \text{w/ pr. } 1 - \iota, \end{cases}$$

[22] We use an inverted exponential distribution, which places a large mass of agents on the right-hand side of the distribution, since an individual's human capital decays over time in the model.

[23] We use the micro data for the CPS (and the corresponding supplements) provided by IPUMS (Flood et al. [2021]). We compute a Mincer style log earnings regression for workers with less than 5 years of potential experience in the CPS. Our Mincer regression includes a quadratic in potential experience as well as occupation, education, gender, race, year fixed effects as well an indicator for working full time. We estimate our Mincer regression on a sample of individuals with real weekly earnings greater than 100 dollars.

[24] As in Herkenhoff et al. [2024], to measure the NLATI ratio for each individual, we sum cash, checking, money market funds, CDs, corporate bonds, government savings bonds, stocks, and mutual funds less credit card debt over annual gross income.

where $\mu = \frac{1}{1+g}$ governs the size of technological decay caused by technology growth, and $\iota \geq 0$ governs the probability of technology decay. To be consistent with the quarterly timing of the model and the annual rate of technology growth g, we set $\iota = 0.25$.

Labor Market and Production. In the labor market, we set the job destruction rate to 5.95% per quarter, $\delta = 0.0595$.[25] When an individual is hit by the separation shock δ they are able to immediately search with probability λ_S. We calibrate the parameter λ_S to match the average unemployment duration of workers in the DWS. For workers that are displaced between 2010 and 2017 in the DWS, the average duration of unemployment was 1.037 quarters.

We use a CRS labor market matching function that returns well-defined job finding probabilities:

$$M(s,v) = \frac{sv}{(s^{\xi} + v^{\xi})^{1/\xi}} \in [0,1).$$

As estimated by Schaal [2017], we set the matching elasticity parameter to be $\xi = 1.6$.

The vacancy posting cost is allowed to vary by occupation. We model the cost of posting a vacancy in an occupation k to be,

$$\kappa(k) = \kappa + \eta \left[\exp\left(c_k - \bar{c}\right) - 1\right] \tag{4}$$

where c_k is the technology intensity of occupation k and $\bar{c}$ is the average level of technology intensity across all occupations. We discuss below how the technology intensity parameters c_k are calibrated, which leaves two parameters to calibrate in equation 4: κ and η. κ is calibrated by targeting an unemployment rate of 6.8%, which is the average reported by the Bureau of Labor Statistics from 2010 to 2017. The parameter η governs the heterogeneity in vacancy costs by occupation, and is calibrated to match the duration of unemployment in the 5th technological change quintile. In the DWS, we find that the average duration of unemployment for workers displaced from the highest quintile of technological change is 1.1 quarters. In Section 3.1, we show the full profile of average unemployment durations across technological change quintiles.

When workers and firms match, they produce according to an "up-to-the-task" production function, as in Albrecht and Vroman [2002] and Jarosch and Pilossoph [2019]. The production function $f(c_k z, h, x)$ is given by

$$f(c_k z, h, x) = \begin{cases} A_x c_k z & A_x h \geq c_k z \\ 0 & \text{o.w.,} \end{cases}$$

where the parameter A_x denotes the relative productivity of workers with experience $x \in$

[25] Using the method from Shimer [2005] and data from the CPS for the years 2010-2017, we estimate a quarterly job separation rate of 5.95%.

$\{E, N\}$. We normalize the relative productivity of inexperienced workers to 1 (i.e., $A_N = 1$). We set the relative productivity of experienced workers to $A_E = 1.12$, which generates a 12% increase in productivity and wages for experienced workers to align with the estimates on the returns to occupation tenure from Kambourov and Manovskii [2009a]. Workers become experienced, on average, after being in an occupation for five-years, which corresponds to a 5% quarterly probability ($\lambda_E = 0.05$). Unemployed workers become inexperienced with probability λ_N. We calibrate the probability that an unemployed worker becomes inexperienced to match the share of individuals who switch occupations after layoff. In the DWS between 2010 and 2017, Braxton and Taska [2023] find that 62% of displaced workers switch occupations following job loss.

Workers' general human capital h also evolves while in the labor market. The human capital grid $\mathcal{H}$ is taken as given by agents and is spaced such that moving up by a grid point is associated with an increase in human capital of $g = 1.5\%$. The general human capital of employed individuals evolves according to

$$H(h, W) = h' = \begin{cases} h\mu & \text{w/ pr. } \iota \\ h & \text{w/ pr. } 1 - \iota. \end{cases}$$

Transfers and Retraining. Unemployed agents receive public insurance transfers from the government b as well as the value of home production d. The value of the public insurance transfer b is calibrated to match the change in transfers to the change in lost earnings as measured in the Panel Study of Income Dynamics (PSID). Using the PSID, Braxton et al. [2024] estimate that public insurance to the unemployed replaces 41.2% of lost earnings. The value of home production d is estimated by targeting the decline in consumption following job loss. Using the PSID, Saporta-Eksten [2013] estimates that consumption declines by 8% following job loss.

The unemployed also have the ability to enroll in a retraining program. The parameters for retraining are set to be consistent with estimates based on retraining occurring through community colleges, which we discuss in greater detail below. The cost of the training program κ_R is calibrated to match the ratio of the tuition cost to average earnings. Using data on community college tuition costs from Kane and Rouse [1999] and average earnings from the CPS, we estimate that a quarter of community college costs 5.12% of average quarterly earnings. The tuition subsidy to retrain is set to zero in the baseline estimation of the model (i.e., $s = 0$). We do so for two reasons. First, Jacobson et al. [2005a] comment that most of the displaced workers in their study attended community college at their own expense. Second, Kambourov et al. [2012] and Osikominu [2013] comment that in the U.S. since the mid-1990s, programs for displaced workers have focused on job search assistance (i.e., getting individuals reemployed quickly) rather than on teaching new skills through retraining.

From the estimates of Kane and Rouse [1999], we set the cost to the government of an additional student enrolled in community college classes to be equal to four-times the costs of tuition to enrolled students (i.e., $\zeta = 4$).[26] The probability of increasing human capital through retraining λ_R is calibrated to match the average increase in earnings for individuals who enroll in community college classes following displacement. Jacobson et al. [2005a] link administrative earnings data to community college records for the state of Washington and estimate that one-year of community college classes increases post-displacement earnings by 9% annually for men and 13% for women. To be conservative, we focus on the earnings gain among men and target an average gain in quarterly earnings of 2.25% per quarter of retraining. The evolution of human capital among unemployed workers who engage in the retraining program ($R = 1$) is given by

$$H(h, U, 1) = h' = \begin{cases} h\mu & \text{w/ pr. } \iota \\ h & \text{w/ pr. } 1 - \iota - \lambda_R \\ h(1+g) & \text{w/ pr. } \lambda_R. \end{cases}$$

The general human capital of unemployed workers who do not enroll in the retraining program ($R = 0$) evolves in the same fashion as employed workers,

$$H(h, U, 0) = H(h, W).$$

The utility cost of enrolling in the retraining program ψ is calibrated to match the share of displaced workers who enroll in community college following displacement. Jacobson et al. [2005a] estimate that 16.6% of displaced workers enroll in community college classes following displacement.

Before discussing the calibration of the remaining parameters, we briefly discuss why we focus on modeling retraining as occurring through community college and how the estimates we use to discipline the retraining portion of the model relate to the literature. Recent evidence by Leung and Pei [2023] and Minaya et al. [2023] suggest that much of the retraining that occurs in the U.S. is performed in community colleges rather than technical centers or the federal WIA program. A key input into our exercise is the gain in earnings from retraining. Kambourov et al. [2012] find similar returns to retraining (not only retraining that occurs via community colleges) in the U.S., while Osikominu [2013] finds similar returns in Germany. These estimates are based on non-experimental data. Using experimental data from the Na-

[26] Kane and Rouse [1999] provide estimates of the costs of enrolling in community college. They estimate the cost to students of one-year of community college to be \$2,300 (in 2012 dollars). The authors comment that the costs of community college are largely borne to the government, and estimate the cost to the government per year of classes is \$9,150 per-student. Their estimates correspond to the year 1997. Using the CPS, we measure average annual earnings in 1997 to be \$44,899.3 (in 2012 dollars).

tional Job Training and Partnership Act Study, Heckman et al. [2000] find comparable gains in earnings resulting from retraining. In a recent paper Hyman [2018], uses quasi-experimental variation in the leniency of judges who rule on Trade Adjustment Assistance (TAA) eligibility to estimate the impact of TAA on worker outcomes and finds that average annual returns to retraining are approximately 9.3% of prior earnings. Finally, recent work by Katz et al. [2022] finds higher returns for "sectoral training programs," however these programs primarily focus on low income and disadvantaged individuals.[27]

Occupations. Finally, we discuss the mapping between occupations in the data and the model. For tractability in the quantitative model, we consider $K = 10$ occupations. As in Braxton and Taska [2023], to map occupations in the data to occupations in the model, we group occupations with similar computer and software requirements together.[28] To obtain the technology intensity in each occupation ($\{c_k\}_{k=1}^{k=10}$), we use variation in earnings across the 10 occupation groups. Since this calibration follows from our earlier work in Braxton and Taska [2023], we relegate the details to Appendix C.1.

Table 1 contains a summary of the model parameters, and Table 2 displays the calibrated parameters and their calibration targets.[29] The estimated model matches the targeted moments very well. In the next section, we provide a series of non-targeted moments to serve as a model validation exercise.

3.1 Non-targeted Moments

In this section, we compare the predictions of the quantitative model to a series of non-targeted moments to serve as a model validation.

Unemployment Duration by Prior Occupation. We start by examining how unemployment duration varies by the rate of technological change in an individuals pre-displacement occupation. To compare estimates from the model to the data, we simulate a DWS in the model. To simulate a DWS in model simulated data, we identify individuals who have been hit by the separation shock within the past three-years and collect their occupation and earnings in

[27]As discussed above, to calibrate the retraining portion of the model requires data on three objects: (1) the cost of the retraining program, (2) the share of displaced workers who would enroll in program and (3) estimates of their program's impact on earnings. Once sufficient data for other forms of training programs, such as the sectoral training programs, becomes available for these three objects, we think it would be interesting to revisit the benefits and costs of subsidized retraining.

[28]In Appendix C.1, we show the cutoffs used to generate the 10 occupation groups.

[29]For ease of exposition, we present the parameter estimates for all of the technology intensity terms in Table 8 in Appendix C.1.

Table 1: Model Parameters

Variable	Value	Description
		Non-calibrated
Variable	Value	Description
g	1.50%	Annual technology growth rate
ι	0.25%	Quarterly probability of technology decay
r	4.00%	Annual risk-free rate
r_b	13.06%	Annual borrowing interest rate
δ	5.95%	Quarterly job separation probability
A_N	1.00	Inexperienced worker productivity
A_E	1.12	Experienced worker productivity
λ_E	5%	Quarterly probability of becoming experienced
ξ	1.6	Labor search match elasticity
s	0	Retraining tuition subsidy
ζ	4	Relative cost to government of retraining
T	120	Life span in quarters
		Jointly-calibrated
Variable	Value	Description
b	0.280	Public insurance transfer to unemployed
κ	0.258	Firm entry cost, level
η	0.692	Firm entry cost, slope
d	0.042	Home production
κ_R	0.034	Tuition cost of retraining
ψ	0.652	Utility cost of retraining
λ_R	0.678	Probability of human capital gain from retraining
λ_N	0.822	Probability of becoming inexperienced when unemployed
λ_S	0.559	Probability of searching after separation
λ_H	0.378	Exponential parameter for initial human capital
c_1	0.554	Technology intensity first occupation
β	0.980	Workers discount factor

Note: Table presents model parameters for the baseline estimation of the quantitative model.

the quarter prior to displacement and their occupation and earnings in the quarter of the "survey." We additionally record the length of an individuals unemployment spell following being hit by the separation shock. Based on an individual's occupation prior to displacement, we form quintiles of displaced workers using the change in technology in their occupation (i.e., the technology intensity (c_k) of their occupation).[30] We then measure the average duration of

[30]For a given change in the frontier technology Δz, occupations with greater technology intensity experience a larger increase in the human capital (skill) requirement necessary to work in that occupation. Consistent with this setup, we showed in Braxton and Taska [2023] that occupations with higher initial levels of computer and software requirements experienced larger increases in computer and software requirements over our sample period (see panel (B) of Figure 1).

Table 2: Model Calibration

Variable	Value	Target	Model	Data	Source
b	0.280	Transfer to income loss	41.0%	41.2%	PSID
κ	0.258	Unemployment rate	7.4%	6.8%	BLS
η	0.692	Average unemployment duration, 5th tech quintile	1.00	1.10	DWS-BG
d	0.042	Consumption upon layoff	91.6%	92.0%	SE
κ_R	0.034	Retraining cost to average earnings	5.1%	5.1%	KR
ψ	0.652	Share retraining after layoff	16.9%	16.6%	JLS
λ_R	0.678	Earnings gain from retraining	2.4%	2.3%	JLS
λ_N	0.678	Share switching occupations after layoff	48.5%	62.0%	DWS
λ_S	0.559	Average unemployment duration after layoff	1.04	1.04	DWS
λ_H	0.378	P75-25 log residual earnings of young workers	0.24	0.38	CPS
c_1	0.554	Ratio of occupation earnings to average earnings	0.80	0.79	CPS
β	0.554	P75 net liquid to assets to income	22.1%	21.1%	SCF

Note: Table presents the calibration of the quantitative model. In the table, KR refers to Kane and Rouse [1999], JLS refers to and Jacobson et al. [2005a], and SE refers to Saporta-Eksten [2013].

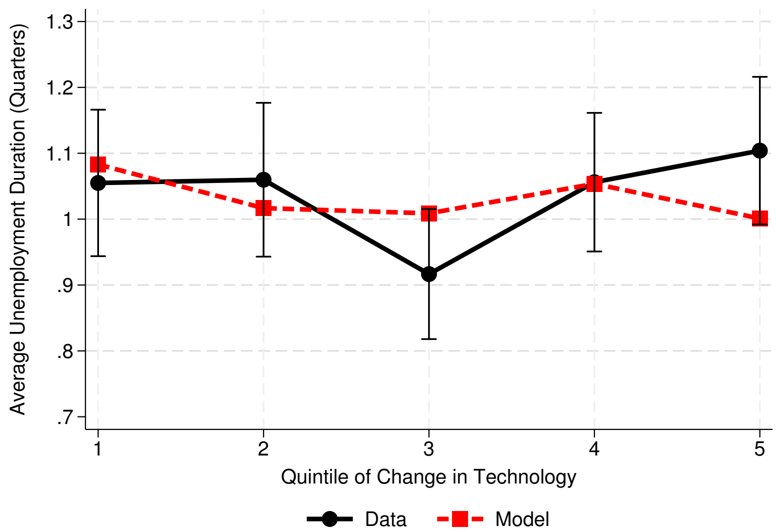
unemployment by quintile and compare to estimates from the DWS.[31] Figure 2 presents the average unemployment duration by quintile of technological change in the DWS (black, solid line with circle markers) and in the quantitative model (red, dashed line with square markers). The quantitative model is able to successfully capture the feature of the data that there is a relatively flat profile of unemployment durations across quintiles of technological change.[32]

Duration Elasticity. In the policy exercise of Section 4 we will compute the optimal transfer and retraining subsidy to the unemployed. A large literature has examined optimal transfers to the unemployed. An influential set of papers by Baily [1978] and Chetty [2006] highlight that the optimality of the current provision of transfers can be tested via a series of sufficient statistics for the consumption drop upon job loss and the elasticity of unemployment duration with respect to transfers, which we hereafter refer to as the duration elasticity. We calibrated our quantitative model to be consistent with the decline in consumption upon job loss. We next examine the quantitative model's ability to generate a duration elasticity that is consistent with the data. To do so, we vary the public insurance transfer rate in our quantitative model and compute the average duration of unemployment. Using this variation, our quantitative model produces a duration elasticity of 0.415. Card et al. [2015] estimate a duration elasticity of 0.35 for the 2003-2007 time period and an estimate in the range of 0.65 to 0.9 during the Great

[31] In Appendix C.2, we show that the quantitative model is able to match the empirical evidence on the heterogeneity in earnings losses by the rate of technological change presented in Section 1.

[32] Note that the average unemployment duration in the 5th quintile is a targeted moment. The other quintiles are untargeted in the calibration of the quantitative model.

Figure 2: Unemployment Duration by Exposure to Technological Change



Notes: This figure presents model and data estimates on the average unemployment duration by quintile of the change in technology in the occupation from which they were displaced. In the model, quintiles are determined based on the technology intensity of individuals' occupation prior to displacement. The solid black line represents estimates from the data, and the dashed red lines represent estimates from the model. The vertical black lines represent 95% confidence intervals of data estimates.

Recession.[33]

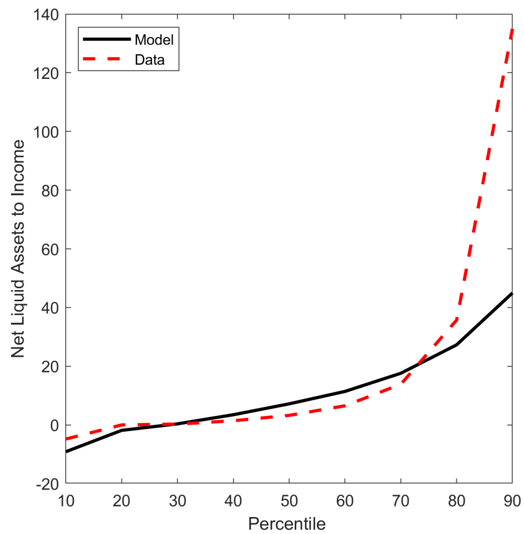
Retraining By Age. Next, we examine how the decision to engage in retraining as well as the effectiveness of retraining vary by the age of the displaced worker. In their companion paper, Jacobson et al. [2005b] report that the rate at which workers enter into community college classes is decreasing by age. In particular, they find that older workers (over the age of 35) are approximately 6 percentage points less likely to enroll in community college class after displacement relative to younger workers (between the ages of 25 and 35). Using these age ranges in our quantitative model, we find that older workers are 8.7 percentage point less likely to enroll in retraining after displacement relative to younger workers. Additionally, Jacobson et al. [2005b] find that the returns to community college classes are similar for younger and older workers in their sample. Our quantitative model generates this pattern with both groups experiencing approximately a 2.3% increase in earnings from one quarter of retraining.

Net Liquid Asset Distribution. Finally, we compare the distribution of net liquid assets in the model and data to examine the degree to which individuals can self-insure via prior savings. In Figure 3, we plot the distribution of net liquid assets in the model (black, solid line) as well as in the data (red, dashed line) as measured in the 2010 and 2013 waves of the SCF. While the

[33] Krueger and Meyer [2002] report a range of estimates on the duration elasticity and report a range of 0.1 to 1.

model is calibrated to match the 75th percentile of the distribution, the figure shows that the model is able to capture the shape of nearly the entire distribution up until the 80th percentile. The model under performs in getting the far right tail of the distribution. However, given the quantitative model's success in matching the bottom 80 percent of the distribution we view this as evidence that the model is able to largely capture the degree of self-insurance that agents have access to.

Figure 3: Net Liquid Asset Distribution



Notes: This figure presents model and data estimates on the distribution of net liquid assets. The black, solid line represents estimates from the model, while the red, dashed line, is from the 2010 and 2013 waves of the SCF.

4 Optimal Policy for Unemployed Workers

In this section, we use the model to perform a policy experiment in which we solve for the optimal public insurance transfer and retraining tuition subsidy for unemployed workers. In our baseline economy, transfers to the unemployed replace 41.0% of lost earnings on average, and the retraining tuition subsidy is set to 0%. We compute the optimal policy for unemployed workers across steady states of the model on the basis of the welfare of a newborn who is "behind the veil of ignorance" (i.e., has not yet realized their initial human capital draw). Let $F(h)$ denote the distribution of initial human capital. Our social welfare function is then given by,[34]

$$\mathcal{W} = \int_h \hat{U}_1^N(h, 0, 0) dF(h) \tag{5}$$

[34]Recall that agents enter into the model as unemployed, inexperienced and with zero assets.

We define the optimal policy to be the transfer to the unemployed b and subsidy to retraining s that maximizes social welfare $\mathcal{W}$, while keeping all other parameters from Table 1 fixed. For ease of presentation, when discussing the optimal public insurance transfer to the unemployed we present it as a replacement rate. We find that the optimal policy sets the replacement rate of public insurance transfers to 51% of lost earnings and the retraining tuition subsidy to 19%.

Optimal Policy. To compute the optimal policy for unemployed workers, we maximize the social welfare criterion in equation 5. To understand the role of adjusting public insurance transfers as well as retraining subsidies, we maximize social welfare under three scenarios: (1) solving for the optimal level of public insurance transfers, holding the current subsidy to retraining programs fixed; (2) solving for the optimal tuition subsidy for retraining, holding current public insurance transfers fixed; and (3) solving for the optimal combination of public insurance transfers and tuition subsidies for retraining.

Table 3 presents the results of the welfare experiment. Column (1) corresponds to the baseline estimation of the model, which represents the current U.S. policy of transfers to unemployed workers replacing 41.0% of lost earnings and a 0% subsidy to the retraining program. Column (2) reports the optimal replacement rate of public insurance transfers to unemployed workers, holding the retraining subsidy fixed at 0%. Welfare is maximized when the public insurance transfer replaces 52.5% of lost earnings. On average, individuals are willing to give up 0.19% of lifetime consumption to be born in an economy with a 52.5% replacement rate rather than in an economy with a 41.0% replacement rate. With more generous public insurance transfers, individuals have higher consumption upon job loss. Additionally, with more generous transfers, unemployed individuals apply for jobs with higher wage piece rates, which increases wages after job loss (among individuals who are employed). However, jobs with higher wage piece rates have a lower job finding rate, which causes the unemployment rate as well as the average unemployment duration to increase. Due to the more generous transfers and the higher unemployment rate, the tax rate on labor income must be raised to maintain a balanced budget. The government balances the welfare gains of greater consumption following job loss with the efficiency losses of higher labor income taxes at a replacement rate of 52.5%.

We next consider the optimal subsidy to retraining programs, holding public insurance transfers fixed; column (3) of Table 3 presents the results. Welfare is maximized when the retraining subsidy is increased to 34%. On average, individuals are willing to give up 0.08% of lifetime consumption to be born in an economy with a 34% retraining subsidy rather than in an economy with no subsidy to retraining. With more generous subsidies to retraining, the share of individuals who enroll in retraining increases. Increased uptake of retraining results in higher earnings after job loss. There are two channels through which retraining increases earnings after job loss, both stemming from the increases in human capital. First, with higher

Table 3: Optimal Policy for Unemployed Workers

	(1) Baseline	(2) Optimal Transfer	(3) Optimal Subsidy	(4) Optimal Combination
Transfer/Income Loss	41.0%	52.5%	41.0%	51.0%
Retraining Subsidy	0%	0%	34%	19%
Welfare Change	-	0.19%	0.08%	0.21%
Consumption Upon Job Loss	91.6%	92.3%	91.6%	92.2%
Earnings After Job Loss	91.9%	92.5%	92.0%	92.4%
Unemployment Rate	7.4%	8.0%	7.4%	7.9%
Unemployment Duration (Qtrs.)	1.04	1.13	1.05	1.11
Share Retraining	16.9%	18.4%	18.6%	19.4%
Pct. Change NPV Consumption	-	0.327%	0.098%	0.334%
Tax Rate	3.59%	4.99%	3.66%	4.80%

Notes: 'Welfare' is the consumption equivalent of leaving an economy with the U.S. policy of a 41.0% *replacement rate and* 0% *subsidy to retraining and moving to an economy with an alternate replacement rate or retraining subsidy. For example, in column (2), the welfare change of* 0.19% *indicates that an individual, on average, would give up* 0.19% *of lifetime consumption to have a* 52.5% *replacement rate as opposed to a* 41.0% *replacement rate, holding the current tuition subsidy fixed. See Appendix D for details on the estimation of the welfare effect. Consumption upon job loss measures consumption in the period of job loss relative to the period before job loss. Earnings after job loss compares earnings before and after job loss using the simulated DWS detailed in Section 3.1. The percent change in NPV consumption compares the NPV of consumption using equation 6 relative to the baseline estimation of the model.*

human capital, some workers are able to remain in their pre-displacement occupation. Second, higher human capital increases job finding rates, ceteris paribus, which both increases the likelihood that workers are employed after job loss and induces workers to adjust their wage search decisions within an occupation by applying for higher wage jobs. Because of these changes in human capital, the introduction of retraining subsidies increases earnings after job loss with only minuscule changes to the unemployment rate or the average duration of unemployment.

While transfers impact consumption immediately upon job loss, retraining and the associated human capital (earnings) gains impact consumption in the periods *following* job loss. To examine this in more detail, we consider the average path of consumption from the period in which an individual is displaced from their job (i.e., when they are hit by the separation shock) through the next 20 quarters. Let $\bar{c}_k$ denote the average value of consumption for individuals who are k periods after displacement, where $k \in [0, 20]$. To succinctly summarize these paths across alternative policies, we compute the net present value (NPV) of each and compare them to the baseline model. Let $NPV(c)$ denote the NPV of consumption around job loss, which is computed as,

$$NPV(c) = \sum_{k=0}^{20} \frac{\bar{c}_k}{(1+r)^k}. \tag{6}$$

Column (3) in Table 3 shows that at the optimal retraining subsidy (holding the public insurance transfer fixed), the NPV of consumption increases by almost 0.1% relative to the baseline model. This increase in the path of consumption after job loss contributes to the welfare gains stemming from increasing retraining subsidies.

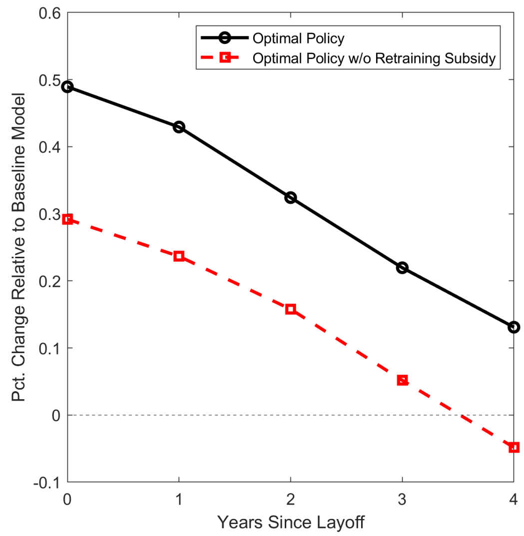
The results presented in columns (2) and (3) of Table 3 show that there are welfare gains from increasing both the generosity of public insurance transfers and the retraining subsidy for unemployed workers. We now examine the optimal combination of public insurance transfers and retraining subsidies to the unemployed; Column (4) of Table 3 presents the results. Social welfare is maximized with public insurance transfers that replace 51% of lost earnings on average and a 19% subsidy for the tuition cost of retraining.[35] On average, individuals are willing to give up 0.21% of lifetime consumption to be born in an economy with the optimal combination of public insurance transfers and retraining subsidies relative to the baseline economy.

The optimal policy includes both transfers to the unemployed as well as subsidies for retraining because each policy insures consumption at different horizons after job loss. In Figure 4, we plot the NPV of consumption under the optimal policy (black, solid line with circle markers) at different horizons after job loss, relative to the baseline economy. In the year of job loss, the NPV of consumption is nearly 0.5% higher under the optimal policy relative to the baseline economy. To decompose the share of this consumption gain that is coming from transfers, we estimate a version of the model where transfers are set to their value in the optimal policy but the retraining subsidy is set to zero. We plot the NPV of consumption around job loss for this counterfactual economy with the red dashed line in Figure 4. From just the increase in transfers alone, consumption is 0.3% higher in the year of job loss. Thus, in the year of layoff, approximately 60% of the gain in consumption is coming from the increase in transfers. From this we argue that in the short-run, transfers provide the majority of additional insurance to the unemployed as part of the optimal policy.

In the subsequent years following job loss, the gain in consumption that is attributable to transfers starts to decline. For example, 3 years after job loss, at the optimal policy the NPV of consumption is approximately 0.2 percent higher relative to the baseline model. However, only 0.05 percent of this increase is attributable to public insurance transfers. While in the 4th year after job loss, all of the increase in consumption is coming through the increase in retraining subsidies. Thus, the majority of the gains in consumption in the optimal policy at these longer

[35] As we discuss in Section 3, the cost to the government of an additional student enrolling in retraining is equal to 4-times the cost of tuition. This is modeled via the parameter ζ. Thus, an alternative interpretation of our optimal policy result is that the overall subsidy to retraining is going from 80% to 83.4% ((83.4% $= 4K_R + 0.19K_R)/5K_R$). We thank an anonymous referee for this insight. For ease of presentation, we continue to focus on the "tuition" subsidy for retraining in the remainder of the paper.

Figure 4: Decomposing Consumption After Job Loss Under Optimal Policy



Notes: This figure presents the net present value (NPV) of consumption around job loss. The net present value of consumption around job loss is calculated using equation 6. In the figure, 0 years after layoff corresponds to the quarter of layoff through 4-quarters after layoff; 1 year after layoff corresponds to 5 through 8 quarters after layoff; 2 years after layoff corresponds to 9 through 12 quarters after layoff; 3 and 4 years after job loss are defined analogously. The black line with circle markers corresponds to the optimal policy, which sets transfers so that they replace 51% of lost earnings with transfers and sets the retraining subsidy to 19%. The red, dashed line, with square markers corresponds to the optimal policy with retraining subsidies set to zero, but transfers set to replace 51% of lost earnings. The net present value in these two scenarios is presented as a percent change relative to the baseline economy.

horizon are coming through the inclusion of retraining subsidies. Thus, we conclude that retraining subsidies help to provide longer-run consumption insurance to the unemployed. Since retraining subsidies and public insurance transfers provide additional consumption insurance at different horizons after job loss they are both included in the optimal policy.

Increasing Retraining Using Only Transfers. Above we showed that increasing retraining via tuition subsidies provides additional consumption insurance after job loss. One could wonder if the same gains via increased retraining could be obtained by further increases in transfers to the unemployed. As we discuss in more detail below, increasing retraining via public insurance transfers alone is: (1) more expensive than doing so via retraining subsidies and hence requires a larger increase in taxes, and (2) is associated with increases in the unemployment rate and unemployment durations. The combination of these two factors generate lower consumption around job loss relative to the optimal policy, which includes retraining subsidies.

At the optimal policy, 19.4% of the unemployed enroll in retraining. Obtaining this rate of retraining via only public insurance transfers, requires increasing the replacement rate of transfer to 59.1% of lost earnings. In Table 4, we compare the outcomes from our optimal pol-

Table 4: Transfers and Increased Retraining

	(1) Optimal Policy	(2) Counterfactual
Transfer/Income Loss	51.0%	59.1%
Retraining Subsidy	19%	0%
Welfare Change	0.21%	-0.08%
Share Retraining	19.4%	19.3%
Tax Rate	4.8%	6.2%
Unemployment Rate	7.9%	8.8%
Unemployment Duration (Qtrs.)	1.1	1.2
Pct. Change NPV Consumption	-	-0.102%

Notes: This table compares the outcomes from the optimal policy found in column (4) of Table 3 with a counterfactual policy that increases public insurance transfers to the level required to match the retraining rate in the optimal policy without using retraining subsidies. Net present values are calculating using 6 and are compared relative to the optimal policy.

icy (column (1)) with a counterfactual policy that increases public insurance transfers to 59.1% and sets the retraining subsidy to zero (column (2)). To finance this level of transfers and target a 19.4% retraining rate, requires increasing the labor income tax rate to 6.2%, while at the optimal policy the tax rate is 4.8%. By construction retraining subsidies are only paid out when an individual opts in to enrolling in retraining, while public insurance transfers are paid to all unemployed workers. Thus, retraining subsidies can be thought of as a more targeted policy tool, which requires smaller increases in taxes compared to public insurance transfers. Additionally, this level of transfers amplifies the moral hazard impacts of transfers to the unemployed. In this counterfactual economy with a 59.2% replacement rate of transfers, the unemployment rate increases to nearly 9% and the average unemployment duration increases to over 1.2 quarters. As consumption is lower among the unemployed relative to the employed, increases in the amount of time that individuals spend in unemployment after layoff reduces the path of consumption following layoff. With the higher level of taxes, and longer unemployment durations, the net present value of consumption around job loss is *lower* under this counterfactual policy compared to the optimal policy by 0.1% percent.[36]

Heterogeneity by Age. We next examine how the optimal policy and the inclusion of retraining subsidies impacts workers of different ages. Table 5 shows that at the optimal policy, the rate of retraining increases for both younger and older workers.[37] Additionally, in column

[36]Additionally, in the counterfactual economy with public insurance transfers replacing 59.1% of lost earnings and zero retraining subsidies, there is a welfare decline of 0.08% (of lifetime consumption) relative to our baseline model.

[37]To align with the definitions in Jacobson et al. [2005b], we define a young worker as a displaced worker between the ages of 25 and 35 and an older worker as a displaced worker over the age of 35.

Table 5: Heterogeneous Effects of Optimal Policy by Age

	(1) Baseline	(2) Optimal Combination	(3) Only Transfers
Transfer/Income Loss	41.0%	51.0%	51.1%
Retraining Subsidy	0.0%	19%	0%
Share Retraining Young	22.8%	24.1%	23.6%
Share Retraining Old	14.1%	17.1%	15.6%
Pct. Change NPV Consumption Young	-	0.446%	0.279%
Pct. Change NPV Consumption Old	-	0.251%	0.068%

Notes: The first column presents results from the baseline estimation of the model, while the second column presents results from the model evaluated at the optimal policy. The third column presents results from the model when the transfer to the unemployed is increased so that it replaces 51% of lost earnings (as in the optimal policy in Table 3), but there are no subsidies for retraining. Net present values are calculating using equation 6 and are compared relative to the baseline policy. As in Jacobson et al. [2005b], we define a young worker as a displaced worker between the ages of 25 and 35, and an older worker as a displaced worker over the age of 35.

(2) of Table 5 we show that consumption is higher following job loss for both younger and older workers at the optimal policy relative to the baseline economy, although the increase in consumption is larger for younger workers.

We next examine the degree to which retraining subsidies drive these results. To do so, in column (3) of Table 5, we estimate the model removing retraining subsidies while keeping transfer to the unemployed fixed at its value from the optimal policy. Retraining rates decline overall, with a larger decline among older workers. Similarly, we find there is a decline in the path of consumption after job loss once retraining subsidies are removed, but the decline is largest for older workers. These results highlight that the inclusion of retraining subsidies provides additional consumption insurance to both younger and older workers, with larger effects among older workers.

Role of Technological Change in Setting Optimal Policy. We now turn off technological change ($g = 0\%$) and perform the policy experiment of solving for the optimal combination of public insurance transfers and retraining subsidies.[38] This exercise allows us to examine how technological change influences the optimal policy for unemployed workers. Column (2) of Panel I in Table 6 presents the optimal policy in an environment without technological change. The optimal policy without technological change replaces 61.9% of lost earnings with transfers and sets the retraining subsidy to 8%. From the comparison of optimal policies with and without technological change, we see that accounting for technological change induces

[38] In Appendix C.3, we discuss how we re-calibrate the model without technological change.

Table 6: Impact of Technological Change on Optimal Policy Displaced Workers

	(1) Baseline	(2) W/o Tech. Change
Technology Growth Rate (g)	1.5%	0%
Panel I		
Optimal Policy: Transfer/Income Loss	51.0%	61.9%
Optimal Policy: Retraining Subsidy	19%	8%
Panel II		
Earnings 5 Yrs. After Job Loss	94.3%	100.4%
Consumption 5 Yrs. After Job Loss	94.0%	99.6%

Notes: The first column presents estimates from the baseline estimation of the model. The second column present estimates from the estimation of the model without technological change. In Panel I, we compare the optimal policy in the environment with technological change (column (1)) and without technological change (column (2)). In Panel II, we compare earnings and consumption losses 5 years after layoff (20 quarters) compared to 4-quarters prior to layoff. These values are normalized as a percent of their pre-layoff values.

the government to expand retraining subsidies as part of the optimal policy for unemployed workers.

Technological change alters the policy response to unemployment because of its impact on the nature of income shocks and their pass-through to consumption. Panel II of Table 6 presents earnings and consumption 5-years after job loss for the baseline version of the model with technological change (column (1)) and the model without technological change (column (2)). The table shows that 5 years after job loss in the model with technological change earnings remain approximately 5.7% below their pre-displacement level. Conversely, without technological change earnings have fully recovered to their pre-displacement level. We observe a similar pattern in consumption following job loss. Without technological change, an individual's consumption exhibits an almost complete recovery within five-years of job loss. Conversely, with technological change, an individual's consumption remains permanently lower after job loss. These permanent declines in consumption are less able to be insured via transfers and increase the motive for retraining subsidies to be included as part of the optimal policy for unemployed workers.

5 Conclusion

In this paper, we examine how technological change impacts the provision of insurance to the unemployed. To answer this question, we develop a Bewley style model with technological change, occupation choice, and employment risk. Using our calibrated model, we find that the government would increase both public insurance transfers and retraining subsidies relative to current U.S. policy. The intuition for this result is that transfers and retraining subsidies insure consumption at different horizons after job loss. Transfers insure consumption upon job loss, while retraining subsidies help to better insure consumption in the years after job loss.

We demonstrate that technological change generates a motive for the government to expand retraining subsidies as part of the optimal policy for unemployed workers in addition to public insurance transfers. Technological change creates a motive for retraining subsidies given their role in shaping long run earnings losses. Without technological change, earnings losses are job loss are less persistent, which allows them to be insured via transfers.

The tractability of the quantitative model in this paper provides several avenues for future work. For example, recent work by Hershbein and Kahn [2018] highlights that technological change accelerates in recessions. Future work can examine the optimal mix of transfers to the unemployed as well as retraining subsidies over the business cycle. Additionally, technological change has important implications for workers of different ages (e.g., Hobijn et al. [2018], Porzio et al. [2022], and Adão et al. [2024]), future work could examine optimal age dependent policies in the face of technological change.

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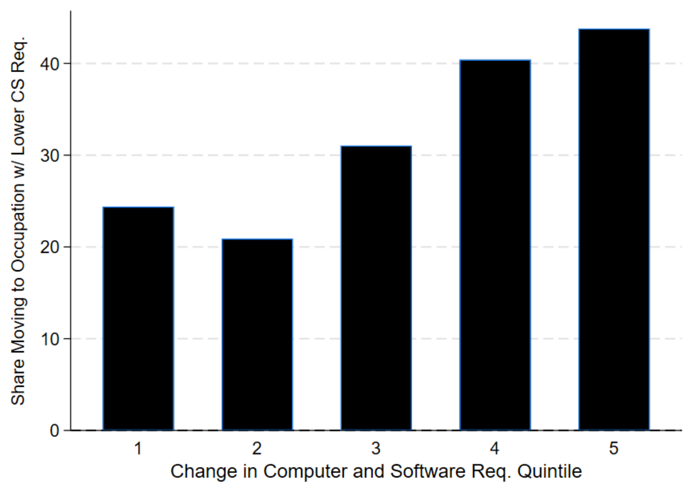
A Additional Empirical Results

In this appendix, we present a series of additional empirical results.

Moving to an occupation with less computer and software requirements. Figure 5 shows the share of individuals who move to an occupation with lower computer and software requirements relative to their original occupation following displacement.[39] In the first quintile, approximately 25% of individuals switch occupations and move to an occupation with lower computer and software requirements. Conversely, nearly 45% individuals displaced from occupations in the fifth quintile move to an occupation with lower computer and software requirements.

Figure 5: Moving to Occupations with Lower computer and Software Requirements



Notes: The figure shows the share of individuals who move to an occupation with lower computer and software requirements relative to their original occupation. Individuals are placed into quintiles based on the occupation from which they were displaced. Occupations are defined using four-digit SOC codes.

B Additional Model Details

In this appendix, we present additional details of the model. We first present the value functions for experienced workers (Appendices B.1 and B.2), as well as firms that are matched with an experienced worker (Appendix B.3). We then prove that the model equilibrium is Block Recursive (Appendix B.4). Finally, we present the solution algorithm for solving the model (Appendix B.5.)

[39] In particular, we compare the share of vacancies that list a computer or software requirements in 2017 for individuals' current occupation and the occupation from which they were displaced. Note in the figure we do not condition on switching occupations. We find similar results if we use the share of vacancies listing computer and software requirements in 2010.

B.1 Bellman Equation for Unemployed Experienced Worker

In this section, we present the Bellman equation for an experienced unemployed worker. Let $U_t^E(a,h,k)$ denote the value of being an age t unemployed worker who is experienced in occupation k, with assets a and human capital h. In the current period the unemployed worker makes their consumption and savings decision, as well as their retraining decision. At the start of the next period, the unemployed worker becomes inexperienced in their current occupation with probability λ_N. After learning if they remain experienced in occupation k, the unemployed worker chooses which occupation as well as wage piece rate to apply for a job in. If the worker is experienced in occupation k, they search for a job in the experienced labor market for occupation k, and in the inexperienced labor market for all other occupations $\tilde{k} \in \mathcal{K}/\{k\}$. The value to an experienced unemployed worker is,

$$U_t^E(h,a,k) = \max_{a' \geq \underline{A}, R \in \{0,1\}} u(c) - R\psi + \beta \mathbb{E}\left[(1-\lambda_N)\hat{U}_{t+1}^E(h',a',k) + \lambda_N \hat{U}_{t+1}^N(h',a',0)\right] \quad \forall t \leq T$$

$$U_{T+1}^E(h,a,k) = 0$$

where $\hat{U}_{t+1}^E(h',a',k)$ denotes the expected value of search for an experienced unemployed worker in the labor market, and is given by,

$$\begin{aligned}\hat{U}_{t+1}^E(h',a',k) = \max\Bigg\{ &\max_{\tilde{\omega}\in[0,1]} p(\theta_{t+1}^E(h',a',k,\tilde{\omega}))W_{t+1}^E(h',a',\bar{z},k,\tilde{\omega}) + \left(1 - p(\theta_{t+1}^E(h',a',k,\tilde{\omega}))\right) U_{t+1}^E(h',a',k); \\ &\max_{(\tilde{k},\tilde{\omega})\in\mathcal{K}/\{k\}\times[0,1]} p(\theta_{t+1}^N(h',a',\tilde{k},\tilde{\omega}))W_{t+1}^N(h',a',\bar{z},\tilde{k},\tilde{\omega}) + \left(1 - p(\theta_{t+1}^N(h',a',\tilde{k},\tilde{\omega}))\right) U_{t+1}^E(h',a',k)\Bigg\}\end{aligned}$$

subject to the budget constraint,

$$c + q(a')a' + R(1-s)\kappa_R \leq b + a + d$$

and the law of motion for a worker's human capital, which is indexed by employment status U and their retraining decision $R \in \{0,1\}$,

$$h' = H(h,U,R)$$

B.2 Bellman Equation for Employed Experienced Worker

In this subsection, we present the Bellman equation for an experienced employed worker. Let $W_t^E(h,a,z,k,\omega)$ denote the value of being an experienced worker with human capital h and assets a, who is employed with a firm in occupation k that uses technology $z \leq \bar{z}$ and is payed piece rate ω. The worker makes their consumption and savings choice, and receives utility from consumption. At the start of the next period, shocks to human capital and match technology are realized, and the worker becomes unemployed with probability δ. Workers who become unemployed get to search with probability λ_S in the labor market. In the labor market, agent's search across occupations and wage price rates. Since the worker is experienced in occupation k, they search for a job in the experienced market for occupation k, and in the inexperienced market for all other occupations $\tilde{k} \in \mathcal{K}/\{k\}$. The continuation value of the worker is,

$$
\begin{aligned}
W_t^E(h,a,z,k,\omega) = \max_{a' \geq \underline{A}} u(c) + \beta \mathbb{E} \Big[& \delta \left(\lambda_S \hat{U}_{t+1}^E(h',a',k) + (1-\lambda_S) U_{t+1}^E(h',a',k) \right) \\
& + (1-\delta) \hat{W}_{t+1}^E(h',a',z',k,\omega) \ \Big] \forall t \leq T
\end{aligned}
$$

$$
W_{T+1}^E(h,a,z,k,\omega) = 0
$$

where $\hat{W}_{t+1}^E(h',a',z',k,\omega)$ denotes the value of on-the-job search for a worker who is experienced in occupation k, and is given by,

$$
\begin{aligned}
\hat{W}_{t+1}^E(h',a',z',k,\omega) = \max \Big\{ & \max_{\tilde{\omega} \in [0,1]} p(\theta_{t+1}^E(h',a',k,\tilde{\omega})) W_{t+1}^E(h',a',\bar{z},k,\tilde{\omega}) + \left(1 - p(\theta_{t+1}^E(h',a',k,\tilde{\omega}))\right) W_{t+1}^E(h',a',z',k,\omega); \\
& \max_{(\tilde{k},\tilde{\omega}) \in \mathcal{K}/\{k\} \times [0,1]} p(\theta_{t+1}^N(h',a',\tilde{k},\tilde{\omega})) W_{t+1}^N(h',a',\bar{z},\tilde{k},\tilde{\omega}) + \left(1 - p(\theta_{t+1}^N(h',a',\tilde{k},\tilde{\omega}))\right) W_{k,t+1}^E(h',a',z',k,\omega) \Big\}
\end{aligned}
$$

subject to the budget constraint,

$$
c + q(a')a' \leq (1-\tau)\omega f(c_k z, h, E) + a
$$

and the laws of motion for worker's human capital, and the firm's technology,

$$
h' = H(h,W) \quad z' = Z(z)
$$

B.3 Bellman Equation for Firm Matched with Experienced Worker

In this subsection, we present the Bellman equation for a firm that is matched with an experienced worker. Let $J_t^E(h,a,z,k,\omega)$ denote the value to a firm in occupation k of being matched with an experienced worker with human capital h, assets a, using technology $z \leq \bar{z}$ where the worker is paid piece rate ω. In the current period, the firm produces and makes wage payments. In the next period, the match can expire due to an exogenous separation, or the worker leaving due to on-the-job search. If the match continues, the firm continues to receive the benefits of the match. The value to the firm is given by:

$$J_t^E(h,a,z,k,\omega) = (1-\omega) f^E(c_k z, h, E) \\ + \frac{1-\delta}{1+r}\mathbb{E}\left[\left(1-p(\theta_{t+1}^{e(\hat{k})}(h^{'},a^{'}(y),\hat{k}(y^{'}),\hat{\omega}(y^{'})))\right) J_{t+1}^E(h^{'},a^{'}(y),z^{'},k,\omega)\right] \quad \forall t \leq T$$

$$J_{T+1}^N(h,a,z,k,\omega) = 0$$

where $p(\theta_{t+1}^{e(\hat{k})}(h^{'},a^{'}(y),\hat{k}(y^{'}),\hat{\omega}(y^{'})))$ is the probability that the worker matches with another firm at their optimal occupation $\hat{k}$ and wage rate $\hat{\omega}$ choice via on-the-job search, and leaves their current match.

B.4 Block Recursive Equilibrium

In this subsection, we prove that the model's equilibrium is Block Recursive (e.g., Menzio and Shi [2011]), i.e. the distribution of workers across states does not impact individual or firms decisions problems, and hence the equilibrium prices.

Suppose that the tax rate τ is given, and that the government's budget constraint is not required to hold. Then the individual, and firm problems can be solved independently of the distribution of individuals across states Ω. In solving the model we iterate on τ to balance the governments budget constraint. We formally define and proof the Block Recursive nature of the model below.

Proposition 1. *Suppose τ is given and the government budget does not need to balance. Assume that the utility function meets standard conditions ($u^{'} > 0, u^{''} < 0, \lim_{c\to\infty} u^{'}(c) = 0$ and u is invertible), the matching function is invertible and constant returns to scale, and there is bounded support for the choice set of occupations $k \in \mathcal{K} \equiv [\underline{k}, \bar{k}]$ and wage piece rates $\omega \in [0,1]$, then a Block Recursive Equilibrium exists.*

Proof. The proof is performed using backward induction. Let $t = T$ and consider an unemployed individual which is inexperienced for the sake of brevity (the proof follows in an identical manner for employed households, as well individuals who are experienced in an occupation). Since the individuals' continuation value is zero for $T+1$ onward, the individual's dynamic programming problem does not depend upon the aggregate distribution across states.

In the terminal period T, agents set their asset choice to zero (i.e. $a_T^{'}(h,a,0) = 0$) and choose to not retrain ($R_T(h,a,0) = 0$), which gives the following continuation values for the terminal period:

$$U_T^N(h,a,0) = u\left(b + a + d\right)$$

Hence, the value to an unemployed (inexperienced) household, does not depend upon the aggregate distribution.

In the labor market, the firm's value function is independent of the aggregate distribution as well, and is given by,

$$J_T^x(h, a, z, k, \omega) = (1 - \omega) f(c_k z, h, x)$$

when the firm is matched with a worker with experience $x \in \{E, N\}$. Given this value to the firm of a match, the labor market tightness will also be independent of the aggregate distribution, and is given by,[40]

$$\theta_T^x(h, a, k, \omega) = p_f^{-1} \left(\frac{\kappa_k}{J_T^x(h, a, \bar{z}, k, \omega)} \right)$$

An unemployed inexperienced individual at age $T - 1$ makes a labor market search choice over occupations $k \in \mathcal{K}$ and wage piece rates $\omega \in [0, 1]$ to solve:

$$\max_{(k,\omega) \in \mathcal{K} \times [0,1]} p(\theta_T^N(h, a, k, \omega)) W_T^N(h, a, \bar{z}, k, \omega) + \left(1 - p(\theta_T^N(h, a, k, \omega))\right) U_T^N(h, a, 0)$$

As long as k and ω are within bounded intervals the extreme value theorem guarantees at least one solution to this problem. The same holds for experienced unemployed individuals as well as employed individuals. Since τ is given the distribution of workers across states does not impact individual's decision problems.

Stepping back from $t = T - 1, ..., 1$, and repeating the above procedure completes the proof.

□

B.5 Solution Algorithm

In this appendix, we present the algorithm for solving the model presented in Section 2. Solving the model proceeds in the following steps:

1. **Taxes:** Guess τ.

2. **Firms Bellman:** Compute the value to a firm of being in a match in the terminal period $J_T^x(h, a, \bar{z}, k, \omega)$ at the value of the frontier technology.[41] Using the value of a firm in the terminal period, invert the free entry condition to obtain labor market tightness $\theta_T^x(h, a, k, \omega)$.

[40] Recall vacancies are only posted for the latest vintage of technology $\bar{z}$.

[41] Note we measure the value at the frontier technology because all matches are formed at the frontier technology in an occupation.

3. **Individual Consumption Savings Problem:** Solve the individuals consumption, savings, and retraining choice problem in the terminal problem.

4. **Individual's Job Search:** Use the estimate of $\theta_T^x(h, a, k, \omega)$ to solve the individual's job search problem.

5. **Repeat for ages** $T-1, T-2, ..., 1$.

6. **Budget Balance:** Simulate a mass of individuals and check that the government's budget constraint is satisfied. Update guess of τ until the government budget is balanced.[42]

C Additional Quantitative Details and Results

In this appendix we provide additional details on the calibration of the quantitative model as well as additional results from the quantitative model. In Appendix C.1, we discuss how we calibrate the parameters related to technology intensity in an occupation. In Appendix C.2, we present a series of non-targeted moments from the model relating to the outcomes of displaced workers. Finally, in Appendix C.3, we discuss the calibration of the model without technological change.

C.1 Calibration of Technology Parameters

In this section, we provide additional details on the calibration of the technology intensity parameters of the model ($\{c_k\}$), which follows from Braxton and Taska [2023]. Calibrating the technology intensity parameters proceeds in two steps: (1) assigning each 4-digit occupation to one of 10 occupation groups, and (2) measuring earnings across the 10 occupation groups. Using estimates of earnings across the 10 occupation groups we calibrate the parameters ($\{c_k\}$).

Fist, we partition the distribution of occupations (in the data) into $K = 10$ groups based on the share of vacancies listing a computer or software requirement in 2010. The groups are formed by evenly spacing grid points in terms of the share of vacancies listing a computer or software requirement in 2010. Table 7 contains the grid points that are in each group. Let $k \in \mathcal{K} = \{1, 2, .., 10\}$ denote an occupation group, and let o denote an occupation at the four-digit SOC code level.

Second, we measure earnings across the occupation groups k. Let $e_{i,o,t}$ be the real earnings of individual i working in occupation o in period t, let $z_{o,2010}$ denote the share of vacancies listing a computer or software requirement in occupation o in the year 2010, and let γ_t denote

[42] In the simulation to check the government's budget balance we simulate 125,000 individuals for 260 periods, 10 times, burning the first 120 periods. We report averages over the 5 simulations.

Table 7: Occupation Groups and Cutoffs

Occupation Group (k)	Min. CPU Req.	Max. CPU Req.
1	0	0.075
2	0.075	0.125
3	0.125	0.175
4	0.175	0.225
5	0.225	0.275
6	0.275	0.325
7	0.325	0.375
8	0.375	0.425
9	0.425	0.475
10	0.475	–

Notes: Table shows the cutoffs used to form the 10 occupation groups in the data. 4-digit occupations are placed into one of the 10 occupation groups based on the share of vacancies listing a computer or software requirement in 2010.

a set of year dummy variables. We estimate the following regression of computer and software requirements on earnings using data from the CPS:[43]

$$e_{i,o,t} = \alpha + \beta z_{o,2010} + \gamma_t + \epsilon_{i,o,t} \tag{7}$$

Using the coefficients from the estimation of equation 7, we compute the predicted earnings for each individual. Let $\hat{e}_{i,o,t}$ denote the predicted earnings for individual i working in occupation o in year t. From these predicted values we estimate average predicted earnings for each occupation group $k \in \mathcal{K}$, which is denoted by $\bar{e}_k$. We use the set of smoothed earnings $\bar{e}_k$ to govern the technology parameters in the model. We calibrate the technology intensity of the first occupation (c_1) to match the ratio of smoothed earnings in the first occupation to average earnings among all workers. We calibrate the remaining technology parameters ($\{c_k\}_{k=2}^{k=10}$) to match the ratio of smoothed earnings in occupation k relative to the first occupation ($\frac{\bar{e}_k}{\bar{e}_1}$). Table 8 contains the parameter estimates of the technology intensity parameters as well as their model fit.

C.2 Model Impact of Technology Growth on Displaced Workers

In this appendix, we analyze additional model's predictions on the role of technology growth on the outcomes of displaced workers. As in Section C.2, these moments were untargeted in the calibration of the model and serve as a model validation exercise.

Panel (a) of Figure 6 shows the average change in earnings following displacement by quin-

[43] In estimating equation 7 we use the outgoing rotation groups of the monthly CPS survey between 2010 and 2017. Earnings are measured as real weekly earnings. To ensure a minimum degree of labor force attachment, we remove individuals with real weekly earnings below $100.

Table 8: Calibration of Technology Intensity Parameters

Variable	Value	Target	Model	Data	Source
c_1	0.554	Ratio of occupation earnings to average earnings	0.802	0.793	CPS
c_2	0.579	Relative Earnings 2nd Occupation	1.060	1.048	CPS
c_3	0.616	Relative Earnings 3rd Occupation	1.115	1.113	CPS
c_4	0.652	Relative Earnings 4th Occupation	1.179	1.184	CPS
c_5	0.684	Relative Earnings 5th Occupation	1.240	1.248	CPS
c_6	0.719	Relative Earnings 6th Occupation	1.293	1.311	CPS
c_7	0.753	Relative Earnings 7th Occupation	1.355	1.368	CPS
c_8	0.789	Relative Earnings 8th Occupation	1.425	1.414	CPS
c_9	0.835	Relative Earnings 9th Occupation	1.494	1.500	CPS
c_{10}	0.933	Relative Earnings 10th Occupation	1.649	1.684	CPS

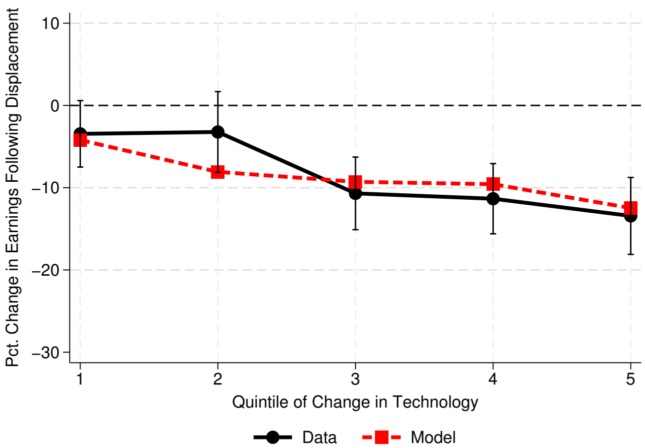
Notes: Table shows parameter estimate for the technology intensity parameters, as well as the model fit. Relative earnings for the k-th occupation is defined as the ratio of earning in the k-th occupation relative to earnings in the first occupation.

tile of the change in technology as estimated in the model (dashed red line) as well as in the data (solid black line). The figure shows that workers in the fifth quintile (those who experience the largest change in technology requirements) experience the largest decline in earnings of over 7% of pre-displacement earnings. Conversely, workers in the first quintile experience the smallest decline in earnings of just over 1% of pre-displacement earnings. These patterns are qualitatively consistent with the estimates from the data, which show that individuals displaced from occupations undergoing larger increases in computer and software requirements experience a larger decline in earnings. As we will discuss in greater detail below, the model generates larger declines in earnings for workers in the occupations experiencing the largest changes in technology, as these workers fall behind the technological frontier for their occupation and then move to an occupation with lower skill requirements, where they are paid a lower wage.

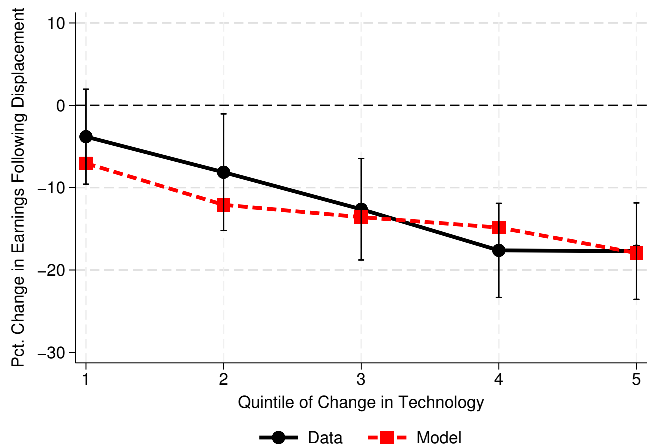
We next examine the model's predictions on the role of occupation switching in the outcomes of displaced workers. Panel (b) of Figure 6 shows the change in earnings by technology change quintile for individuals who switch occupations following job loss, while panel (c) shows the change in earnings among individuals who do not switch occupations. The figure shows that the model is able to replicate the empirical observation that occupation switchers incur larger declines in earnings compared to occupation stayers. Occupation switchers incur large losses in the model, as occupation switching after job loss occurs when an individual has fallen behind the technological frontier for their occupation and no longer has the skills to work in their prior occupation. The worker then directs their search to an occupation where their skills are still employable, but they make a permanently lower wage. This induces occupation switchers to have large declines in earnings in the model. Conversely, among occupation stay-

Figure 6: Earnings Around Displacement by Exposure to Technological Change

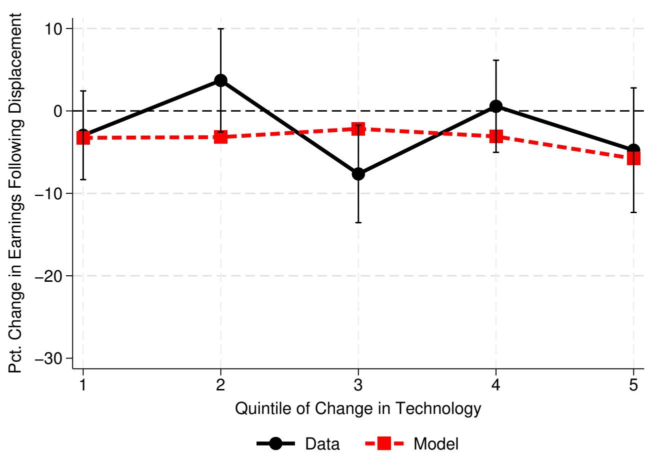
(a) Change in Earnings



(b) Change in Earnings: Occupation Switchers



(c) Change in Earnings: Occupation Switchers



Notes: This figure presents model and data estimates on the outcomes of displaced workers by quintile of the change in technology in the occupation from which they were displaced. In the model, quintiles are determined based on the technology intensity of individuals' occupation prior to displacement. The solid black line represents estimates from the data, and the dashed red lines represent estimates from the model. The vertical black lines represent 95% confidence intervals of data estimates.

ers, in both the model and the data, the size of the change in technology does not significantly affect the size of earnings losses.

The results of this section showed that the estimated model qualitatively captures the empirical patterns documented in Section 1. In particular, in the model individuals displaced from occupations that undergo a larger increase in technology experience a larger decline in earnings, and the decline in earnings is concentrated among occupation switchers.

C.3 Calibration of Model Without Technological Change

In this section, we discuss the calibration of the model without technological change ($g = 0\%$). In calibrating the model without technological change, there are some parameters we hold fixed at their values from the baseline estimation while others are recalibrated. In particular, we keep the technology intensity parameters $\{c_k\}_{k=1}^{k=10}$ fixed at their values from the baseline estimation. In the model without technological change individuals are significantly less likely to switch occupations following displacement (under 5% without technological change vs. nearly 50% with technological change). The parameter λ_N which governs the probability that an experienced worker looses their experience while unemployed disciplines the share of individuals who switch occupations in the baseline estimation of the model. Given the low rate of occupation switching in the model with without technological change, we keep the parameter λ_N at its value of the baseline estimation of the model. Finally, technological change impacts the distribution of workers general human capital in the model. To make the distribution of human capital consistent across estimations of the model in the model without technological change individuals draw their human capital from the stationary distribution of human capital from the baseline version of the model where retraining has been turned off. We use the estimation of the model with retraining removed to capture how initial human capital should be distributed. The remaining parameters are calibrated as in the baseline estimation of the model. Table 9 presents the results of this estimation exercise.

D Welfare Calculation

In this section, we describe our process for performing the welfare calculation.

Let $(\{c_t^j, R_t^j\}_{t=1}^{t_{max}})$ be the consumption, and retraining policy functions for an individual j over their lifetime under the baseline policy (i.e. public insurance transfer and subsidy to retraining tuition costs) for unemployed workers. Let $(\{\tilde{c}_t^j, \tilde{R}_t^j\}_{t=1}^{t_{max}})$ be the consumption, and retaining policy functions for an individual j under an alternative policy for unemployed workers. We will perform welfare calculations by estimating the share of lifetime consumption an individual would be willing to forgo (or must receive) to leave the baseline economy and move to an economy with an alternative policy for unemployed workers. Formally, we estimate the

Table 9: Calibration Without Technological Change

Variable	Value	Target	Model	Data	Source
b	0.280	Transfer to income loss	41.5%	41.2%	PSID
κ	0.292	Unemployment rate	6.9%	6.8%	BLS
η	0.734	Average unemployment duration, 5th tech quintile	1.06	1.10	DWS
d	0.003	Consumption upon layoff	92.4%	92.0%	SE
κ_R	0.035	Retraining cost to average earnings	5.2%	5.1%	KR
ψ	0.589	Share retraining after layoff	17.3%	16.6%	JLS
λ_R	0.311	Earnings gain from retraining	2.1%	2.3%	JLS
λ_S	0.571	Average unemployment duration after layoff	1.01	1.04	DWS
β	0.983	P75 net liquid to assets to income	16.7%	21.1%	SCF

Notes: Table shows parameter estimate from calibrating the model without technological change. ($g = 0\%$). In the table, KR refers to Kane and Rouse [1999], JLS refers to and Jacobson et al. [2005a], and SE refers to Saporta-Eksten [2013].

scaling factor for consumption λ_j that makes individual j indifferent between living under either policy:

$$\sum_{t=1}^{T} \beta^t \left(\frac{\left(\lambda_j c_t^j\right)^{1-\sigma} - 1}{1-\sigma} - \psi R_t^j \right) = \sum_{t=1}^{T} \beta^t \left(\frac{\left(\tilde{c}_t^j\right)^{1-\sigma} - 1}{1-\sigma} - \psi \tilde{R}_t^j \right) \tag{8}$$

Solving equation (8) for λ_j returns:

$$\lambda_j = \left[\frac{\sum_{t=1}^{T} \beta^t \left(\frac{\left(\tilde{c}_t^j\right)^{1-\sigma}}{1-\sigma} - \left(\psi \tilde{R}_t^j - \psi R_t^j\right) \right)}{\sum_{t=1}^{T} \beta^t \left(\frac{\left(c_t^j\right)^{1-\sigma}}{1-\sigma} \right)} \right]^{\frac{1}{1-\sigma}} \tag{9}$$

We use the model to simulate a large mass of individuals under a series of alternative policies for unemployed workers. Let N denote the number of individuals that we simulate. For each simulated individual, we estimate λ_j, the scaling factor for consumption that makes the individual indifferent between living under the alternative policy for unemployed workers and the baseline policy. To convert the units of the scaling term λ_j into the percentage of lifetime consumption the individual would be willing to forgo (or must receive), hereafter referred to as lifetime consumption equivalents and denoted $\tilde{\lambda}_j$, we perform the following transformation:

$$\tilde{\lambda}_j = 100(\lambda_j - 1)$$

Let $\{\{\tilde{\lambda}_j\}_{j=1}^{N}\}$ denote the set of lifetime consumption equivalents from the simulation of an alternative policy for unemployed workers. From the distribution of lifetime consumption equivalents, we measure the welfare effect for an alternative policy. The welfare effect for an alternative policy, which is denoted $Welfare$, is measured as:

$$Welfare = \frac{1}{N}\sum_{j=1}^{N}\tilde{\lambda}$$