*American Economic Review 2023, 113(2): 279–316*
*https://doi.org/10.1257/aer.20210182*

# Technological Change and the Consequences of Job Loss†

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*We examine the role of technological change in explaining the large and persistent decline in earnings following job loss. Using detailed skill requirements from the near universe of online vacancies, we estimate technological change by occupation and find that technological change accounts for 45 percent of the decline in earnings after job loss. Technological change lowers earnings after job loss by requiring workers to have new skills to perform newly created jobs in their prior occupation. When workers lack the required skills, they move to occupations where their skills are still employable but are paid a lower wage.* (*JEL* J24, J31, J63, O33)

A large empirical literature has documented that job loss causes a large and persistent decline in earnings (e.g., Jacobson, LaLonde, and Sullivan 1993; Couch and Placzek 2010; and Davis and von Wachter 2011). Separately, a voluminous literature has shown that technological change has reshaped the labor market and played a central role in rising income inequality (e.g., Krusell et al. 2000; Autor, Levy, and Murnane 2003; and Autor and Dorn 2013). In this paper, we explore the role of technological change in explaining the large and persistent decline in earnings following job loss. We find that technological change accounts for over 45 percent of the decline in earnings after job loss.

Our theory is that technological change increases worker productivity if the worker has the skills to use the new technology. Hence, technological change introduces new skill requirements into newly created jobs within an occupation. Not all workers have these new skills, however. If displaced, workers who do not have the new skills that have now become common in their occupation are forced to search for a job in another occupation with lower skill requirements, which tend to be lower paying.

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†Go to https://doi.org/10.1257/aer.20210182 to visit the article page for additional materials and author disclosure statements.

We formalize this theory in a simple two-period model of the labor market with technological change. The model makes stark predictions about the impact of technological change on the outcomes of displaced workers. In particular, it predicts that workers who are more exposed to technological change suffer larger declines in earnings following job loss. The model highlights occupation switching as the central mechanism. Workers who are more exposed to technological change are more likely to switch occupations, and the larger earnings losses of workers who are more exposed to technological change are concentrated among occupation switchers.

We empirically test the theory by estimating the impact of technological change on the outcomes of displaced workers. Using detailed skill requirements from the near universe of vacancies posted online, we create an estimate of within-occupation technological change by measuring the change in computer and software requirements by occupation over time.[1] Consistent with our theory of technological change, we show that workers who are displaced from occupations that are more exposed to technological change (i) experience larger declines in earnings following job loss and (ii) are more likely to switch occupations following job loss. Further, we show that the larger decline in earnings following exposure to technological change is concentrated among occupation switchers.

The theory posits that technological change increases the productivity, and therefore the earnings, of workers who have the skills to use the new technology. We examine this view by investigating the evolution of earnings among *occupation stayers*. We find that among occupation stayers, those who are more exposed to technological change experience larger earnings gains. This result highlights that technological change increases earnings gains for one group of workers (e.g., occupation stayers) while simultaneously making earnings losses more severe for another group of workers (e.g., displaced workers).

Finally, we extend and quantify our model to decompose the source of earnings losses after displacement and estimate the share of earnings losses attributable to technological change. In the quantitative model, workers direct their search for jobs over occupations that differ in the technology used in production as well as wage piece rates. Search over wage piece rates introduces a wage (job) ladder into the model. Additionally, workers have general and occupation-specific human capital, both of which evolve over their working careers. We calibrate the quantitative model to match aggregate labor market moments and show that the model successfully replicates our empirical finding that workers displaced from occupations undergoing greater increases in technology experience larger earnings losses and that the larger earnings losses are concentrated among occupation switchers. In the model, technological change increases the skill (human capital) requirements to work in newly created jobs within an occupation, and occupations experience heterogeneous changes in skill requirements. The model generates large and persistent earnings

[1] We follow recent work by Hershbein and Kahn (2018) and Atalay et al. (2020), who argue that the skill requirements listed in vacancy postings are informative about the technology of the firm posting the vacancy. We choose computer and software requirements as our measure of technological change as innovation in the workplace commonly occurs via changes in computers and software (e.g., Arora, Branstetter, and Drev 2013 and Branstetter, Drev, and Kwon 2019). Additionally, this follows prior work in the macroeconomics and labor economics literature that uses the spread of computers as a measure of technological change (e.g., Berman, Bound, and Griliches 1994; Autor, Katz, and Krueger 1998; and Katz and Autor 1999).

losses when workers are displaced and, as a result of technological change, no longer have the required skills to work in their original occupation. These unemployed workers then direct their search for a new job to an occupation with a lower level of technology used in production where their skills are still employable but wages are lower.

Given the quantitative model's ability to generate earnings losses after displacement that are consistent with the data, we use the model to decompose the source of earnings losses. We estimate the relative importance of a given channel by removing that feature from the model and measuring the average size of earnings losses generated by the model. We find that technological change accounts for over 45 percent of the decline in earnings after job loss. The loss of occupation-specific human capital (34.5 percent) and moving lower on the wage (job) ladder (20 percent) account for the remaining earnings losses after job loss. This result highlights that technological change plays a central role in earnings losses after displacement.

This paper contributes to the vast literature that aims to understand the large and persistent declines in earnings following job loss, as documented by Jacobson, LaLonde, and Sullivan (1993); Couch and Placzek (2010); and Davis and von Wachter (2011).[2] Prior work has shown that occupation switching plays a central role in the persistent decline in earnings following job loss (e.g., Stevens 1997; Kambourov and Manovskii 2009; and Huckfeldt 2022). Recently, Huckfeldt (2022) shows that earnings losses after displacement are concentrated among individuals who transition to a lower-paying occupation. While occupation switching has been known to be a key contributor to earnings losses after displacement, research examining the factors that lead individuals to switch occupations after job loss has been limited. We find that workers who are more exposed to technological change are more likely to switch occupations after displacement. Further, we find that earnings losses after displacement are concentrated among workers who are transitioning out of occupations that are exposed to technological change. Our results complement Huckfeldt (2022) by providing evidence that workers transition to lower-paying occupations, and suffer persistent earnings losses, because within-occupation technological change makes it so that they no longer have the skills to work in their prior occupation. This result highlights that retraining may play a role as part of an optimal policy for displaced workers. More broadly, this paper contributes to the literature by highlighting that technological change is a common force that generates larger earnings gains for some workers (e.g., occupation stayers) but larger earnings losses for other workers (e.g., displaced workers).

Our work also contributes to the recent literature that aims to reconcile the predictions of quantitative models of the labor market with the empirical evidence on earnings declines after job loss.[3] Following the work of Ljungqvist and Sargent (1998), a common method for generating persistent earnings losses in quantitative models is to introduce human capital declines following job loss. Our results suggest that modeling human capital declines upon job loss can be rationalized as individuals

[2] Recent papers empirically examining the costs of job loss in the United States include Flaaen, Shapiro, and Sorkin (2019) and Lachowska, Mas, and Woodbury (2020).

[3] Davis and von Wachter (2011) show that the canonical search and matching model in the spirit of Mortensen and Pissarides (1994) cannot account for the size and persistence of earnings losses following job loss.

falling behind a growing technological frontier. The paper from this literature that is most closely related to ours is Huckfeldt (2022), who generates persistent earnings losses via occupation switching. In the steady-state of Huckfeldt (2022), occupation switches occur when declines in human capital during unemployment move a worker's human capital below the skill requirements of their prior occupation. In our paper, persistent earnings losses occur following displacement when technological change raises the skill requirements to work in an individual's prior occupation and they transition to a lower-paying occupation where their skills are still employable. Additionally, relative to Huckfeldt (2022) our quantitative model includes a wage ladder as well as occupation-specific human capital.[4] Finally, our quantitative model contributes to this literature by nesting several leading explanations for the cost of job loss (e.g., occupation switching, human capital declines, and moving lower on the wage ladder) in a model of the labor market that integrates technological change, occupation choice, and employment risk as well as providing a decomposition of the sources of earnings losses after displacement.[5] We find that technological change accounts for over 45 percent of earnings losses after displacement. The model attributes significant but smaller roles to the loss of occupation-specific human capital (34.5 percent) and moving lower on the wage (job) ladder (20 percent).

This paper also contributes to the large literature that examines the impact of technological change on labor markets (e.g., Autor, Katz, and Krueger 1998; Krusell et al. 2000; Autor, Levy, and Murnane 2003; Autor and Dorn 2013; Hershbein and Kahn 2018; and Deming and Noray 2020).[6] This literature has primarily focused on how technological change has shaped trends in employment and income inequality. In a related paper, Deming and Noray (2020) examine how the rapid pace of newly introduced skill requirements in occupations that are concentrated in STEM majors (science, technology, engineering, and mathematics) accounts for the flattening of the earnings profile for workers employed in these STEM occupations over their first ten years in the occupation. We add to this literature by showing both empirically and quantitatively that technological change also plays a central role in earnings losses after displacement.

The paper proceeds as follows. Section I presents a simple two-period model of technological change and labor markets. Section II introduces the data used in this paper, while Section III introduces our measure of technological change. In Section IV, we present our primary empirical results relating technological change to the outcomes of displaced workers. Section V presents the quantitative model and decomposes the sources of earnings losses after displacement. Finally, Section VI concludes.

[4] Huckfeldt (2022) incorporates aggregate productivity shocks, which are not present in our model.

[5] Krolikowski (2017); Jung and Kuhn (2019); and Jarosch (2021) emphasize the importance of workers engaging in a lengthy process of reclimbing the job ladder in contributing to persistent earnings losses after job loss.

[6] A closely related recent literature examines how occupations change over time in terms of their task and skill requirements and explores the implications for income inequality and worker sorting across occupations (e.g., Lindenlaub 2017; Burstein, Morales, and Vogel 2019; and Atalay et al. 2018, 2020). Recent work has also used patents to measure technological innovation and examine the implications for earnings dynamics (e.g., Kogan et al. 2020). A recent literature has also examined the impact of automation on wages and inequality (e.g., Acemoglu and Restrepo 2018; Arnoud 2018; Leduc and Liu 2020; and Moll, Rachel, and Restrepo 2022). While automation is the replacement of workers with a new technology, the focus of this paper, technological change, is about the introduction of new technologies that increase worker productivity conditional on the worker having the skills to use the technology.

## I. Simple Model of Technological Change

In this section, we present a simple two-period model of the labor market with technological change. This simple model makes predictions about the impact of technological change on the outcomes of displaced workers, which we will use to guide our empirical analysis. In Section V, we extend and quantify the simple model to decompose the source of earnings losses after displacement and estimate the share of earnings losses due to technological change.

Consider a two-period economy where there are two occupations that differ in the level of technology used in production. Let $z_k$ denote the level of technology in an occupation $k$, and let $L$ and $H$ denote the two occupations, where $z_L < z_H$. Assume that $z_L = (1 - \eta) z_H$, where $\eta > 0$ denotes the relative technological distance between occupations in the first period. As we discuss in more detail below, in the second period a new technology $z'_H$ is introduced in the high-technology occupation.[7] For ease of exposition, the introduction of the new technology is unexpected by agents; however, the predictions of the model are identical if it is anticipated.

Workers are risk neutral and heterogeneous in their human capital (skill) $h$, which we think of as general human capital. Let $F(h)$ denote the cumulative distribution function of the human capital distribution. Workers enter into the model as unemployed and proceed to the labor market where they direct their search for jobs over occupations ( $z_L$ and $z_H$). When a worker and a firm are matched with one another, production occurs according to an "up-to-the-task" production function (e.g., Albrecht and Vroman 2002 and Jarosch and Pilossoph 2019), which defines the output of the match as

$$f(h,z) = \begin{cases} z, & \text{if } h \geq z; \\ 0, & \text{otherwise.} \end{cases}$$

This production function requires workers to have a minimum amount of human capital to produce with a given technology. We use the up-to-the-task production function as it introduces a notion of skill requirements, based on technology, to work in a given occupation. We additionally assume that the job-finding rate in an occupation $z$ is equal to one if $h \geq z$ and zero otherwise. When matched with a firm, workers receive a share $\omega \in (0,1)$ of production as a wage.[8] In this model, a worker's occupation search decision is governed by a cutoff rule where workers with human capital such that $h \geq z_H$ apply for jobs in the high-technology occupation $(z_H)$, and workers with human capital such that $h < z_H$ apply for jobs in the low-technology occupation $(z_L)$.[9] Finally, at the end of the first period, a share $\delta$ of agents are displaced and become unemployed.[10]

[7] We introduce the new technology into the high-technology occupation $(z_H)$ as we will show in Section III that occupations with higher initial levels of technology experience larger increases in technology.

[8] We assume a common wage piece rate $\omega$ and job-finding rate equal to one for qualified workers (i.e., $h \geq z$) for ease of exposition. The predictions of the simple model are robust to both assumptions. In the quantitative model in Section V, workers search over occupations and wage piece rates $\omega$, where search frictions are governed via firms' free-entry decision. Search over wage piece rates introduces the notion of a wage (job) ladder into the model. In the quantitative model, we also distinguish between general and occupation-specific human capital.

[9] We prove the existence of the cutoff rule for occupation search in online Appendix A.

[10] If agents are unemployed when production and wage payments occur, they receive a transfer $b$, where we assume $b < \omega z_L$. In the quantitative model, we will calibrate transfers to the unemployed $(b)$ to align with recent US data.

At the start of the second period, suppose that a new technology $z_H'$ is introduced into the high-technology occupation, where $z_H' = (1 + \gamma)z_H$ for $\gamma > 0$. Once the new technology is introduced, all vacancies in the high-technology occupation use the new technology $(z_H')$, while existing matches continue to use the old technology $(z_H)$. This form of technological change is *embodied* in matches, as in Mortensen and Pissarides (1998); Violante (2002); Postel-Vinay (2002); and Eyigungor (2010). With technological change occurring through new matches, the introduction of the new technology does not generate layoffs into unemployment. We make this modeling decision to align with the displaced worker literature that examines the cost of job loss following exogenous layoffs.[11]

We next discuss the implications for displaced workers following the introduction of the new technology. First, consider workers who were displaced from the occupation that did not introduce the new technology. These workers direct their search to the low-technology occupation and incur no earnings losses upon regaining employment. Next, consider workers who were displaced from the occupation that introduced the new technology. Following the introduction of the new technology, there is an increase in skill requirements for newly created jobs in the high-technology occupation. Workers who were employed in the high-technology occupation in the first period but do not have the skills to work with the new technology (i.e., $z_H' > h \geq z_H$) search for a job in the low-technology occupation and suffer a decline in earnings. Alternatively, workers who have the skills to use the new technology (i.e., $h \geq z_H'$) search for a job in the high-technology occupation where the new technology is used in production and experience an increase in earnings. Define $\pi = \frac{F(z_H') - F(z_H)}{1 - F(z_H)}$ as the share of individuals who were employed in the high-technology occupation in the first period who do not have the skills to use the new technology.

From this two-period model, we can make several predictions about the impact of technological change on the outcomes of displaced workers:[12]

- **Model Prediction 1:** If $\pi > \gamma/(\eta + \gamma)$, then workers displaced from the occupation that introduced the new technology experience larger earnings losses, on average, than workers displaced from the occupation with no change in technology.
- **Model Prediction 2:** Workers displaced from the occupation that introduced the new technology are more likely to switch occupations following displacement (i.e., $\pi > 0$).
- **Model Prediction 3:** The larger earnings losses for workers displaced from the occupation that introduced the new technology are concentrated among occupation switchers.

The simple two-period model predicts that exposure to technological change generates larger earnings losses after displacement, with occupation switching playing a central role. Consistent with the results of Huckfeldt (2022), the model predicts

[11] In Section IVE, we show that the probability of displacement is independent of an occupation's exposure to technological change.

[12] Proofs of these predictions are in online Appendix A.

that earnings losses are concentrated among workers transitioning to a lower-paying occupation. Further, the model illuminates technological change as an explanation for why a worker would transition to a lower-paying occupation after displacement. The model also provides an alternative interpretation of a common modeling device for generating earnings losses upon job loss. Following the work of Ljungqvist and Sargent (1998), quantitative models often use declines in human capital during unemployment spells to generate large and persistent declines in earnings following job loss. The simple model highlights that technological change causes some workers to fall behind a technological frontier for their occupation, which then creates a *relative* decline in their human capital, leading them to move to an occupation where their human capital is still employable but where they incur persistent earnings losses. This highlights that the "upskilling" of tasks and obsolescence of skills can be thought of as two sides of the same coin related to technological change.[13]

In the sections that follow, we empirically test these model predictions. In Section V, we extend and quantify the theory to estimate the share of earnings losses that are due to technological change. In the next section, we discuss the data that we will use to empirically test the predictions of the simple two-period model and quantify the theory.

## II. Data

To test the predictions of the model from Section I, we require a measure of technological change by occupation as well as a sample of displaced workers where we observe an individual's earnings and occupation both before and after displacement. In this section, we give an overview of the data used in the paper.

### A. *Measuring Technological Change with Online Vacancies*

First, we discuss the database of skill requirements from online vacancies, which we will use to measure technological change. Burning Glass Technologies (hereafter, Burning Glass) provided us with their database of online vacancy postings. Burning Glass examines approximately 40,000 online job boards and company websites daily to collect information on vacancy posting. Their algorithms identify newly posted ads, remove duplicate advertisements, and collect detailed information about the occupation, employer, and location, as well as the skill and education requirements for the posted vacancy. Given the breadth of coverage, Burning Glass believes their database covers the near universe of jobs that are posted online.[14]

The database of vacancies for this paper covers the years 2007–2017.[15] For each vacancy, the occupation (up to a six-digit Standard Occupational Classification (SOC) code) is recorded along with detailed information on the skill requirements.

[13] An alternative interpretation of the simple model's second prediction is that technological change decreases a worker's ability to remain in their original occupation (even with a common job separation rate [$\delta$]). In online Appendix C.6, we show empirical results consistent with this prediction among a broad sample of workers.

[14] Recent papers using the Burning Glass database include Deming and Kahn (2018); Hershbein and Kahn (2018); Hazell and Taska (2018); Hershbein, Macaluso, and Yeh (2018); Azar et al. (2019); Deming and Noray (2020); and Azar et al. (2020).

[15] In online Appendix C.9, we use a similar database based on vacancies listed in newspapers between 1982 and 2000 provided by Atalay et al. (2020).

Burning Glass collects the text posted for each job vacancy, and their algorithms code keywords and phrases as additional job requirements. Thousands of specific skills are codified, such as knowledge of Microsoft Excel, and are available for each vacancy collected. During our sample period, Burning Glass recorded information for, on average, 1.4 million vacancies per month, each with over eight skill requirements.[16]

As we discuss in Section III, we use changes over time in the skill requirements collected by Burning Glass to estimate technological change by occupation. A benefit of using the Burning Glass database is that it allows us to estimate technological change occurring through newly posted vacancies, which is consistent with the setup of the model in Section I.

### B. *Current Population Survey Displaced Workers Supplement*

In this section, we discuss our sample of displaced workers. To measure the outcomes of displaced workers, we use the Current Population Survey (CPS) Displaced Workers Supplement (DWS). The DWS is well suited to test the predictions of the model from Section I as it contains a sample of displaced workers and occupation information both before and after displacement.[17]

The DWS is conducted every two years as part of the January or February CPS. Individuals are identified as displaced workers and included in the DWS if they have lost their job within the past three years because of their company or plant shutting down, their shift or position being eliminated, or having insufficient work.[18] These reasons for becoming unemployed are designed to identify workers who lost their job for reasons that are exogenous to their characteristics. The DWS collects information on individuals' earnings and occupation both for the job from which they were displaced and for their current job if they are employed at the time of the survey. We use the 2010, 2012, 2014, 2016, and 2018 waves of the DWS, and to align with the Burning Glass data, examine individuals who were displaced from their job between 2007 and 2017.[19]

In the following section, we discuss how we measure technological change at the occupation level. We then empirically examine the predictions of the simple model on technological change and the outcomes of displaced workers presented in Section I.

[16] Hershbein and Kahn (2018) benchmark the Burning Glass data against other measures of vacancy posting (e.g., the Job Opening and Labor Turnover Survey) as well as measures of occupation employment and find that the Burning Glass data have greater coverage of more highly skilled occupations relative to lower skilled occupations. In an earlier draft of this paper (Braxton and Taska 2021), we conduct a similar analysis using data through 2017 and find similar results. Hershbein and Kahn (2018) also find that the representativeness of the Burning Glass data is stable over time.

[17] In the displaced worker literature, authors often use matched employee-employer datasets and identify displaced workers from mass layoff episodes (e.g., Jacobson, LaLonde, and Sullivan 1993; Davis and von Wachter 2011; Couch and Placzek 2010; among others). This approach is not well suited for this paper as matched employee-employer datasets for the United States (e.g., Longitudinal Employer-Household Dynamics (LEHD), Social Security Administration Master Earnings File (SSA)) often do not include occupation information.

[18] Additionally, since the 1998 wave of the DWS, individuals who identify as being displaced are also not self-employed and do not expect to be recalled to their job within the next six months.

[19] We use the CPS DWS provided by IPUMS (e.g., Flood et al. 2021).

## III. Measuring Technological Change

In this section, we discuss the construction of our measure of technological change using the Burning Glass database. We then discuss which occupations have been the most and least exposed to technological change and the characteristics of occupations that are associated with greater exposure to technological change.

To estimate technological change by occupation, we examine the spread of computers and software within an occupation. We focus on computer and software requirements as our measure of technological change as innovation in the workplace commonly occurs via changes in computers and software (e.g., Arora, Branstetter and Drev 2013 and Branstetter, Drev, and Kwon 2019).[20] Following Hershbein and Kahn (2018), we define a vacancy as containing a computer or software related skill if any of its reported skill requirements include the keyword "computer" or if any of the reported skill requirements are classified by Burning Glass as a software skill. We then measure for each occupation the share of vacancies in a given year that contain a computer or software related skill. Let $z_{o,t}$ denote the share of vacancies in occupation $o$ and year $t$ that contain a computer or software related skill. In our baseline analysis, we categorize occupations using four-digit SOC codes as in Hershbein and Kahn (2018) but show that our results are robust to alternative occupation classifications.

To examine whether the share of vacancies in an occupation listing a computer or software requirement is informative about the use of computers and software in that occupation, we compare the estimates from Burning Glass with data from O*NET (Occupational Information Network). O*NET asks individuals working in a given occupation as well as occupational experts to rate the level of knowledge needed in an occupation for a given set of skills/tasks and has been commonly used to measure the tasks performed in an occupation (e.g., Acemoglu and Autor 2011). The level of knowledge is scored 0–7, with higher values indicating that a greater level of knowledge is required. Panel A of Figure 1 compares the share of vacancies listing a computer skill requirement ($y$-axis) to the level of computer knowledge recorded in O*NET ($x$-axis) for each four-digit occupation.[21] The graph shows that our measure of computer and software requirements based on the skill content listed in online vacancies is highly correlated with the measure from O*NET.[22] This finding suggests that the share of vacancies listing a computer or software requirement is informative about the use of computers and software in an occupation.

[20] Prior work has also used the spread of computers as a measure of technological change (e.g., Berman, Bound, and Griliches 1994; Autor, Katz, and Krueger 1998; and Katz and Autor 1999). In online Appendix C.2, we examine the impact of changes in other skill requirements (e.g., cognitive, social, and manual) on the outcomes of displaced workers.

[21] We use vintage 15.1 of O*NET to measure computer usage by occupation (the O*NET variable is 2.C.3.a), which contains data collected between 2005 and 2010. We use this vintage because the midpoint of the data collection period aligns with the initial year of data from Burning Glass (2007). Deming and Kahn (2018) conduct a similar exercise for cognitive and social skills and find that estimates produced from the Burning Glass database align with estimates from O*NET.

[22] The 2007 American Community Survey (ACS) employment-weighted correlation is 0.677.

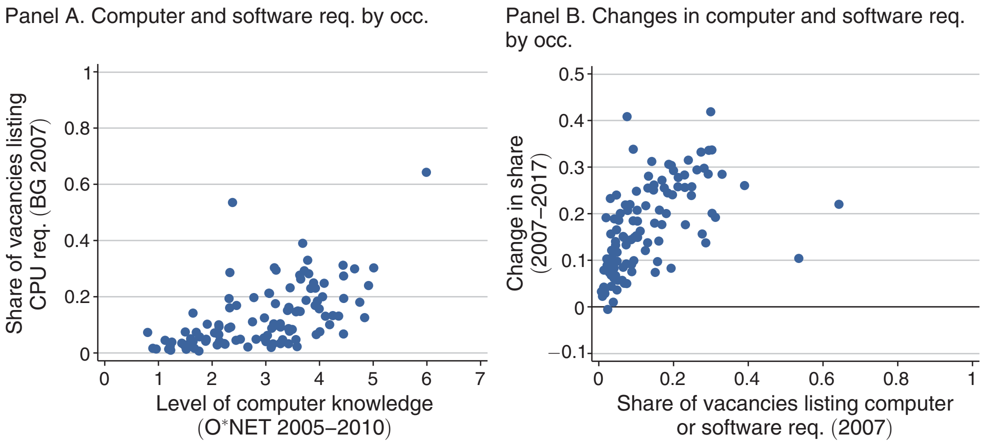


Figure 1. Technological Change by Occupation

*Notes:* Panel A displays the level of knowledge in computers reported in O*NET ($x$-axis) and the share of vacancies listing a computer or software requirement by occupation as measured in the Burning Glass database in 2007 ($y$-axis). Panel B displays the share of vacancies listing a computer or software requirement by occupation in 2007 ($x$-axis), and the change in the share of vacancies listing a computer or software requirement between 2007 and 2017 ($y$-axis) as measured in the Burning Glass database. Occupations are measured using four-digit SOC codes.

Given the measure $z_{o,t}$ of computer and software requirements in each occupation, we estimate technological change by measuring the change in the share of vacancies in a given occupation that contain a computer or software skill. Let $\Delta z_o = z_{o,2017} - z_{o,2007}$ denote the change in the share of vacancies in occupation $o$ that list a computer or software skill requirement between 2007 and 2017. Panel B of Figure 1 presents a scatterplot of computer and software requirements in 2007 ($x$-axis) against the change in computer and software requirements between 2007 and 2017 by occupation ($y$-axis). This scatterplot highlights two important features of the data. First, the scatterplot shows that nearly all occupations saw an increase in computer and software requirements between 2007 and 2017. Second, the scatterplot shows that there is significant heterogeneity in the adoption of computer and software requirements across occupations between 2007 and 2017. This variation in the adoption of computer and software requirements is critical for our identification of the impact of technological change on the outcomes of displaced workers, as we will compare the outcomes of workers displaced from occupations with large increases in computer and software requirements to the outcomes of workers displaced from occupations with a small increase in computer and software requirements.[23]

[23] In online Appendix B.5.1 we compare changes in computer and software requirements in the Burning Glass data to changes in O*NET and show that occupations that have seen larger increases in computer and software requirements as measured in the Burning Glass database have also seen larger increases in O*NET. While changes in computer requirements in Burning Glass and O*NET are correlated, there are subtle differences in what the data measure. Burning Glass data reflect the skills that employers demand at a moment in time, whereas O*NET data reflects the skills that incumbent workers use in an occupation when the occupation is surveyed in O*NET. Hence, changes in Burning Glass data reflect changes in the skills that employers demand, whereas changes in O*NET reflect changes in the skills that incumbent workers use when they are employed in an occupation. We view the Burning Glass measure as being more closely aligned with our model of technological change in Section I; for that reason, we use the Burning Glass data for our baseline measure of technological change.

Table 1—Changes in Computer and Software Requirements by Occupation

| Rank | SOC-4 | Occupation | Chg. computer req. (2007–2017) (1) | Nonroutine cognitive (2) | Routine cognitive (3) | Nonroutine manual (4) | Routine manual (5) |
|---|---|---|---|---|---|---|---|
| *Panel A. Occupations with largest increase in computer and software requirements* | | | | | | | |
| 1 | 1710 | Architects | 0.419 | 1.603 | 0.657 | −0.187 | −0.285 |
| 2 | 3310 | Supervisors of protective service workers | 0.408 | 1.036 | 0.160 | 1.845 | −0.250 |
| 3 | 3390 | Protective service workers | 0.338 | −0.656 | 1.160 | −0.966 | −1.036 |
| 4 | 1720 | Engineers—aerospace/biomedical/computer | 0.337 | 0.323 | −0.468 | −1.587 | −0.868 |
| 5 | 4330 | Financial clerks | 0.336 | −0.705 | 1.878 | −0.633 | −0.311 |
| 6 | 1721 | Engineers—industrial/mechanical/nuclear | 0.332 | 0.644 | −0.084 | −2.095 | −0.558 |
| 7 | 1520 | Mathematical science occupations | 0.315 | 0.888 | −0.789 | −2.455 | −1.355 |
| 8 | 4750 | Oil, gas, and mining extraction workers | 0.312 | −0.290 | 0.340 | 0.635 | 2.158 |
| 9 | 1120 | Advertising, marketing, and sales managers | 0.306 | 1.815 | −1.540 | 0.419 | −1.506 |
| 10 | 2740 | Media and communication equipment workers | 0.304 | 0.097 | 0.605 | −0.235 | 1.112 |
| *Panel B: Occupations with smallest increase in computer and software requirements* | | | | | | | |
| 1 | 3990 | Personal care and service workers | 0.044 | −0.641 | −2.490 | 0.894 | −1.245 |
| 2 | 3730 | Grounds maintenance workers | 0.042 | −1.010 | −2.386 | 0.091 | 2.112 |
| 3 | 5130 | Food processing workers | 0.041 | −0.832 | 0.150 | −0.736 | 1.281 |
| 4 | 3720 | Cleaners | 0.039 | −1.992 | −1.330 | −1.225 | 0.647 |
| 5 | 3920 | Animal trainers and caretakers | 0.036 | −0.234 | −1.760 | 1.154 | −0.706 |
| 6 | 3520 | Cooks and food preparation workers | 0.033 | −1.209 | −0.585 | −0.059 | 1.085 |
| 7 | 3590 | Restaurant attendants, dishwashers, hosts | 0.029 | −1.758 | −1.242 | −0.041 | 0.762 |
| 8 | 4730 | Helpers, construction trades | 0.022 | −0.624 | −0.228 | −0.214 | 1.099 |
| 9 | 3530 | Food and drink servers | 0.010 | −1.040 | −0.394 | 0.210 | 0.214 |
| 10 | 5330 | Drivers—ambulance/bus/tractor trailer/taxi | −0.005 | −1.207 | 0.476 | 2.487 | 1.323 |

*Notes:* Table presents the ten occupations with the largest increase in computer and software requirements between 2007 and 2017 (panel A) and the ten occupations with the smallest increase (panel B). Column 1 presents the change in the share of vacancies listing computer and software requirements by occupation between 2007 and 2017, as measured in the Burning Glass data. Measures of the task content of an occupation presented in columns 2–5 are from Acemoglu and Autor (2011). Occupations are classified using four-digit SOC codes.

### A. *Which Occupations Are Exposed to Technological Change?*

In this section, we examine which occupations have been more exposed to technological change as measured by changes in computer and software requirements over time. To understand which types of workers are exposed to technological change, we then examine how occupation characteristics (e.g., task content, education, etc.) relate to our measure of technological change.

Table 1 presents the four-digit SOC occupations with the largest and smallest changes in computer and software requirements between 2007 and 2017.[24] The occupations with the largest increases in computer and software requirements include architects, engineers, advertising and marketing managers, as well as protective service workers and their supervisors. Across these occupations we see different types of computer and software requirements being introduced. Among advertising and marketing managers there has been an increase in the demand for specific software packages and platforms. For instance Salesforce, Software as a Service (SaaS), and Google Analytics/Google AdWords are forms of software and platforms that were commonly listed in vacancies in 2017 but were rarely seen in 2007. Conversely, protective service jobs frequently include data entry by 2017, and job postings now list general computer skills and experience working with spreadsheets. The occupations with the smallest increases in computer and software requirements include drivers,

[24] In online Appendix B.1, we present the change in computer and software requirements using broader two-digit SOC occupation categories.

restaurant workers (servers, attendants, and cooks), personal care and service workers, as well as animal trainers.

To further examine the characteristics of occupations that have been more/less exposed to technological change, we show in columns 2–5 of Table 1 measures of the task content of an occupation developed by Acemoglu and Autor (2011) based on O*NET data.[25] Each index is constructed to be mean zero and have unit variance, with larger values of the index representing an occupation having greater task content in that index (e.g., nonroutine cognitive task content). In column 2 of Table 1, we include the measure of nonroutine cognitive task content for each occupation. Among the ten occupations with the largest increases in computer and software requirements, the majority of occupations (7) are above average in their nonroutine cognitive task content. Column 3 of Table 1 shows that for the three occupations with below-average nonroutine cognitive skill content, they each have above-average routine cognitive skill content.[26] Hence, occupations more exposed to technological change tend to be cognitive occupations, consistent with the notion that new technologies often complement cognitive jobs.

Conversely, among occupations with the lowest increase in computer and software requirements, all ten occupations have below-average nonroutine cognitive task content (column 2), and a majority of the occupations (8) are below average in routine cognitive task content (column 3). Columns 4 and 5 of Table 1 show the nonroutine manual and routine manual task content of each occupation, respectively. Occupations with the least exposure to technological change tend to be more manual task intensive, especially among routine manual tasks.[27]

We conclude this section by discussing the characteristics of workers more/less exposed to technological change. In Figure A3 in online Appendix B.2, using data from the ACS, we show that occupations that are more exposed to technological change tend to employ more highly educated, older, and White workers. Alternatively, we find that the gender composition of an occupation is uncorrelated with exposure to technological change.[28] In the next section, we use our measure of technological change and data from the DWS to examine how exposure to technological change affects the outcomes of displaced workers.

[25] Acemoglu and Autor (2011) construct a measure of the nonroutine cognitive analytic as well as the nonroutine cognitive interpersonal task content of an occupation. We combine their estimates into a single measure of the nonroutine cognitive task content of an occupation by averaging the two measures.

[26] Hershbein and Kahn (2018) also show that routine cognitive occupations have experienced larger increases in computer and software requirements.

[27] In online Appendix B.2, we present binned scatterplots using the measures of task content from Acemoglu and Autor (2011). Using data on all occupations, we find results consistent with those presented here. In particular, occupations with higher cognitive skill content (both routine and nonroutine) have experienced larger increases in computer and software requirements, while occupations with high manual task content have seen the smallest increases in computer and software requirements.

[28] Additionally, in online Appendix B.3, using data on employment and earnings from the ACS, we show that exposure to technological change is not associated with changes in employment share. However, occupations that are more exposed to technological change have experienced both greater earnings growth and a larger increase in within-occupation earnings dispersion.

## IV. Impact of Technological Change on Displacement Outcomes

In this section, we merge the measure of technological change presented in Section III into a sample of displaced workers to test the predictions of the simple two-period model. Consistent with the predictions of the model, we find that individuals displaced from occupations that are more exposed to technological change experience larger declines in earnings and are more likely to switch occupations. Additionally, we find that the larger earnings losses occur among occupation switchers. These results highlight that technological change contributes to the decline in earnings following job loss and works through occupation switching.

### A. *Sample of Displaced Workers*

We start by discussing the construction of the sample that will be used in our empirical analysis. Starting from the DWS, we merge in information on the change in computer and software requirements between 2007 and 2017 in the occupation from which an individual was displaced. In our baseline analysis, we use the four-digit SOC occupation classification as in Hershbein and Kahn (2018). We show that our results are robust to alternative occupation classifications.

To examine the impact of technological change on earnings losses following displacement, we construct a sample of all individuals between the ages of 25 and 65 who are employed both at the time of the DWS and prior to displacement. We additionally require that individuals have non-top-coded earnings both prior to displacement and after displacement.[29] This results in a sample of 6,742 individuals.

The first column of Table 2 contains summary statistics for our sample of displaced workers. We observe, on average, individuals two years after being displaced. These individuals, on average, have weekly real earnings that are over 10 percent below their predisplacement earnings.[30] Additionally, column 1 of Table 2 shows that 63.1 percent of displaced workers who have regained employment at the time of the DWS are employed in a different (four-digit SOC) occupation than the one from which they were displaced.[31]

[29] Some individuals report being employed but also report zero earnings. To be in the sample, we require that an individual have real weekly earnings greater than $100 (in 2012 dollars) both prior to displacement and after displacement. Our results are robust to different values of this minimum earnings threshold. Earnings are deflated using the consumer price index.

[30] An average decline of 10 percent of predisplacement earnings two years following job loss is smaller than the estimates of Davis and von Wachter (2011), who estimate an earnings decline of approximately 16 percent of prior earnings for expansion periods. There are two discrepancies between our sample and the one used by Davis and von Wachter (2011). First, Davis and von Wachter (2011) restrict their sample to individuals who have at least three years of tenure at the firm from which they are displaced. Second, we require individuals to be employed both prior to and following displacement, whereas Davis and von Wachter (2011) make no requirements about regaining employment. Using the DWS, Huckfeldt (2022) obtains a similar estimate of the average decline in earnings following job loss (8.5 percent of prior earnings). Compared to Huckfeldt (2022), we do not condition our sample on working full-time both before and after job loss.

[31] The high percentage of individuals switching occupations is not specific to displaced workers. In online Appendix C.6, using the CPS outgoing rotation groups (ORG) over this time period we find that 36.4 percent of individuals switch occupations over a 12-month period. Using a coarser definition of occupations (13 occupations), Fujita (2018) also finds that over 50 percent of individuals switch occupations after an unemployment spell.

Table 2—Summary Statistics

| | Displaced (1) | CPS nondisplaced (2) |
|---|---|---|
| Change in computer requirements | 0.161 | 0.159 |
| Weekly real earnings (displaced job) | $849.42 | — |
| Weekly real earnings (current job) | $759.62 | $889.64 |
| Years since displacement | 2.02 | — |
| Weeks unemployed after displacement | 15.34 | — |
| Switch occupation (d) | 0.631 | — |
| Age | 41.64 | 43.10 |
| Years of education | 13.95 | 14.14 |
| Observations | 6,742 | 44,994 |

*Notes:* See Section IIB for sample selection criteria. Weekly earnings are measured in 2012 dollars. Occupation switching is measured between the occupation from which individuals were displaced and their current occupation, where occupation is measured using a four-digit SOC code. The symbol (d) denotes a dummy variable.

Column 2 of Table 2 presents summary statistics for nondisplaced individuals from the monthly CPS.[32] Nondisplaced workers are employed in occupations that experienced a similar average increase in computer and software requirements as in our sample of displaced workers.[33] Nondisplaced workers are approximately one and one-half years older than our sample of displaced workers, and have similar years of completed education. The primary margin in which our sample of displaced workers differs from nondisplaced workers is their current weekly earnings. Nondisplaced workers have average weekly earnings of nearly $890, whereas our sample of displaced workers (who have regained employment) have average weekly earnings of almost $760. This comparison suggests that our sample of displaced workers is not selected from particular occupations and is generally similar to the sample of nondisplaced workers.

### B. *Empirical Approach*

In this section, we present our empirical approach for examining the impact of exposure to technological change on the outcomes of displaced workers.

Let $Y_{i,o,t}$ denote the outcome variable of interest for individual $i$, who was displaced in occupation $o$ and is in the DWS in year $t$ (such as the change in log real earnings after displacement, or an indicator for switching occupations, etc.). Let $\Delta \tilde{z}_o$ denote the change in the share of vacancies listing computer or software requirements for occupation $o$ between the years 2007 and 2017, normalized to be mean zero and have unit standard deviation.[34] Let $\mathbf{X}_{i,t}$ denote a vector of controls,

[32] To identify nondisplaced individuals, we consider the DWS waves of the CPS and identify individuals who do not report being a displaced worker within the past three years. To be consistent with the construction of the samples from the DWS, we additionally require individuals to be currently employed with real weekly earnings of at least $100 (in 2012 dollars) and to be non-top-coded. These earnings conditions require us to only use the CPS-ORG, which limits the sample size to a quarter of the monthly CPS.

[33] In Section IVE, we examine how exposure to technological change affects the probability of being displaced and find that exposure to technological change does not have an impact on the probability of displacement.

[34] We perform this normalization so that the coefficient $\beta$ can easily be interpreted as the impact of a one standard deviation exposure to technological change.

which includes the change in the employment share of occupation $o$ between 2007 and 2017, the age of the displaced worker, the log duration of the worker's unemployment spell after layoff, tenure prior to layoff, the level of computer requirements in 2007 in the occupation the worker was displaced from, and years of educational attainment, as well as a series of dummy variables including gender, the survey year, the year of displacement, an indicator for working full-time prior to displacement, and an indicator for working full-time at the time of the survey.[35] The specification we use is of the form

$$Y_{i,o,t} = \alpha + \beta \Delta \tilde{z}_o + \Gamma \mathbf{X}_{i,o,t} + \epsilon_{i,o,t}. \tag{1}$$

Using the specification in equation (1) and our sample of displaced workers, we next test the predictions of the simple model on the impact of exposure to technological change on the outcomes of displaced workers.

### C. *Earnings Following Displacement*

In this section, we test Model Prediction 1 that workers who are more exposed to technological change experience larger earnings losses.

We first provide graphical evidence for the relationship between exposure to technological change, as measured by the change in computer and software requirements over time, and earnings losses among displaced workers. In Figure 2, we present a binned scatterplot of the change in computer and software requirements by four-digit SOC code on the $x$-axis and the average change in log earnings after displacement by occupation on the $y$-axis.[36] The figure shows that, on average, workers displaced from occupations that are more exposed to technological change experience larger declines in earnings.[37] For workers displaced from occupations with no change in computer and software requirements over time, earnings decline by just over 5 percent following job loss. Conversely, workers who are the most exposed to technological change experience a decline in earnings of over 20 percent, on average. Hence, Figure 2 shows that there is substantial variation in the average size of earnings losses by occupation, and this variation is in part explained by an occupation's exposure to technological change. This figure provides strong graphical support for Model Prediction 1 that workers who are more exposed to technological change experience larger earnings losses.

Table 3 presents the results of estimating equation (1) where the dependent variable is the change in log earnings after displacement.[38] The negative coefficient

[35] We control for the initial level of computer and software requirements in an individual's predisplacement occupation so that identification of the impact of exposure to technological change occurs among individuals who were in occupations with similar initial levels of computer and software requirements but experience heterogeneous changes in computer and software requirements over the sample period.

[36] Figure A11 in online Appendix C.11.1 presents a weighted scatterplot with all four-digit SOC occupations.

[37] The red line in Figure 2 represents a linear trend from a regression of changes in computer and software requirements on the average change in log earnings after displacement. The $t$-statistic on the slope of the trend line is -2.96.

[38] To remove the impact of outliers on the estimation results, we winsorize the change in log earnings at the 2.5 percent level. We find similar results at different levels of winsorizing and with the raw data. Additionally, in estimating equation (1), we are using the change in computer and software requirements between 2007 and 2017, whereas the change in earnings occurs during this time period depending on when the individual was laid off. In

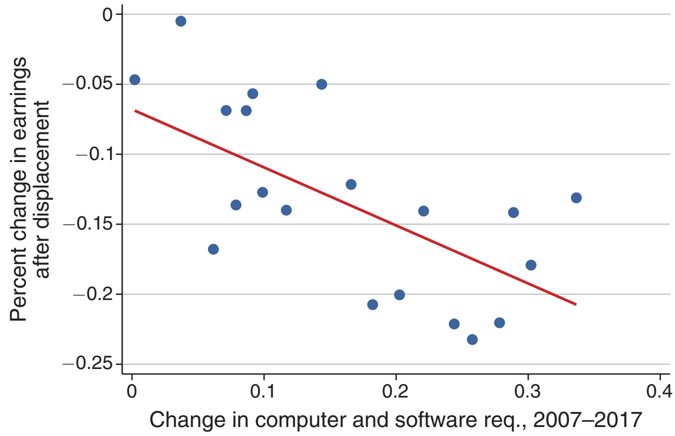


Figure 2. Technological Change and Earnings Losses after Displacement

*Notes:* The figure shows a binned scatterplot of the change in computer and software requirements between 2007 and 2017 by occupation, as measured in the Burning Glass data ($x$-axis), and the average change in log earnings after displacement by occupation, as measured in the DWS ($y$-axis). Occupations are classified using four-digit SOC codes.

on the change in computer requirements in column 1 indicates that an increase in computer and software requirements in the occupation from which an individual was displaced results in larger earnings losses following displacement. Comparing a displaced worker who is one standard deviation above the mean change in computer and software requirements with a worker who is one standard deviation below, we see that, on average, the worker who is one standard deviation above the mean experiences a decline in earnings that is over 7 percentage points larger. The result presented in column 1 suggests that technological change as measured through changes in computer and software requirements contributes to the decline in earnings following job loss.

A potential concern with these results is that the occupations that are undergoing greater technological change may be using the introduction of new technologies as a means to replace workers, and our results simply reflect a decline in the demand for workers in the occupations that are increasing their use of technology. To account for this potential explanation, we include the change in the share of total employment in an occupation between 2007 and 2017 as a control variable in equation (1).[39] Column 2 of Table 3 presents the results after including changes in employment share in the estimation. The coefficient on the change in employment share is positive, indicating that workers displaced from expanding (contracting) occupations suffer smaller (larger) earnings losses on average; however, the coefficient is not

online Appendix C.8, we show that our results are robust to an alternative timing assumption for measuring an individual's exposure to technological change. Finally, in the regression, observations are weighted using weights designed for the DWS to the CPS and provided by IPUMS. In online Appendix C.11.4, we show that our results are robust to using alternative weights.

[39] The change in employment share by occupation is measured using the 2007 and 2017 ACS. The correlation (weighted by the 2007 ACS employment share) between the change in employment share in an occupation and the change in computer and software requirements is 0.005.

Table 3—Technological Change and Earnings Losses after Displacement

| Dependent variable: change in log earnings after displacement | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| *Change in computer requirements* | −0.0354 | −0.0345 | −0.0315 | −0.0259 | −0.0228 |
| | (0.0114) | (0.0122) | (0.0127) | (0.00913) | (0.0102) |
| *Change in employment share* | | 0.00821 | 0.00649 | 0.00604 | 0.00199 |
| | | (0.0108) | (0.00953) | (0.0125) | (0.00909) |
| Observations | 6,742 | 6,742 | 4,267 | 6,742 | 4,267 |
| $R^2$ | 0.234 | 0.234 | 0.063 | 0.233 | 0.062 |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Occupation definition | SOC-4 | SOC-4 | SOC-4 | AD | AD |
| | Full sample | Full sample | Full-time only | Full sample | Full-time only |

*Notes:* The table shows regression results from the estimation of equation (1), where the dependent variable is the change in log earnings after displacement. Earnings are measured in 2012 dollars. The change in computer and software requirements is measured between 2007 and 2017 using the Burning Glass data, and the change in employment share is measured between 2007 and 2017 using the ACS. The change in computer requirements and employment share are both normalized to be mean zero and unit standard deviation. Controls include the age of the displaced worker, the log duration of the worker's unemployment spell after layoff, tenure prior to layoff, the level of computer requirements in 2007 in the occupation the worker was displaced from, and years of educational attainment, as well as a series of dummy variables including gender, the survey year, the year of displacement, an indicator for working full-time prior to displacement, and an indicator for working full-time at the time of the survey. Clustered standard errors are in parentheses, where the clustering is performed at the occupation level. Columns 1–3 classify occupations by four-digit SOC code, while columns 4 and 5 classify occupations by Autor and Dorn (2013) occupation codes.

statistically significant. Additionally, the results in column 2 show that incorporating changes in employment share in the estimation leaves the coefficient on changes in computer and software requirements nearly unchanged. Hence, our result that workers more exposed to technological change have larger earnings losses is not driven by these occupations lowering their demand for workers.

In columns 1 and 2, we measure the change in log earnings after displacement for both full-time and part-time workers. One could then wonder if the results in columns 1 and 2 are being driven by workers more exposed to technological change being more likely to transition to part-time work after displacement. In column 3, we restrict our sample to workers who are employed full-time both before and after displacement. Among these workers, declines in earnings can be attributed to a decline in wages. The coefficient on the change in computer requirements is negative and statistically significant, indicating that workers displaced from occupations that are more exposed to technological change experience a larger decline in wages following displacement.[40]

Finally, we examine the robustness of our results to the classification of occupations. In columns 1–3 of Table 3, we classify occupations using four-digit SOC codes. In columns 4 and 5, we present the results from estimating equation (1)

[40] Prior work by Altonji, Smith, and Vidangos (2013); Lachowska, Mas and Woodbury (2020); and Huckfeldt (2022) finds that wage declines rather than decreases in hours are the main cause of earnings losses after displacement. Additionally, in online Appendix C.11.3, we show that workers who are more exposed to technological change are *less* likely to lose full-time work after displacement. This result provides further evidence that declines in wages rather than hours account for the larger earnings losses of workers who are more exposed to technological change.

where occupations are classified using Autor and Dorn (2013) occupation codes. The negative and statistically significant coefficients on the change in computer and software requirements in columns 4 and 5 show that our result that workers who are more exposed to technological change suffer larger earnings losses is robust to alternative occupation classifications.

The results presented in Table 3 provide strong empirical support for Model Prediction 1 that workers who are more exposed to technological change experience larger earnings losses after displacement. In online Appendix C.1, we show that we find similar magnitudes for the impact of exposure to technological change on earnings losses after displacement among workers of different ages, genders, education levels, and lengths of their unemployment spell.[41] The finding that exposure to technological change has a similar impact on earnings after displacement for workers of different ages, genders, education levels, etc., suggests this is a broad-based phenomenon.[42]

### D. *Mechanism: Occupation Switching*

The results in the previous section show that workers who are more exposed to technological change experience larger earnings losses, a finding that aligns with Model Prediction 1 from Section I. In this section, we examine the mechanisms through which exposure to technological change affects earnings following displacement. The simple model highlights occupation switching as playing a central role in generating larger earnings losses for workers who are more exposed to technological change (Model Predictions 2 and 3). In this section, we test these predictions of the model.

We first test Model Prediction 2 that workers who are more exposed to technological change are more likely to switch occupations following displacement. Panel A of Figure 3 presents a graphical representation of the regression in equation (1) where the dependent variable is switching occupations after displacement. The figure shows that workers displaced from occupations that are more exposed to technological change are more likely to switch occupations after displacement.

Table 4 presents the results of estimating equation (1) where the dependent variable is an indicator for switching occupations following displacement. We consider two alternative classifications for occupations to determine occupation switching: four-digit SOC codes (columns 1and 2) and Autor and Dorn (2013) occupation codes (column 3). The positive coefficient in column 1 indicates that an increase in computer and software requirements in the occupation from which an individual was displaced increases the probability that the individual is re-employed in a different occupation. When we compare a displaced worker who is one standard deviation above the mean change in computer and software requirements with a worker who is

[41] We do not find statistically significant differences across these groups.

[42] In online Appendix C.2, we examine the impact of changes in a broad measure of skill requirements from Deming and Noray (2020) as well as changes in other skill requirements (e.g., cognitive, social, and manual skills) on earnings losses after displacement. While we find results similar to those in Section IVC for changes in broad skill requirements, when we separately examine specific skill changes we find that it is computer and software requirements that have the largest impact on the outcomes of displaced workers. In particular, we only find some evidence that increases in cognitive skill requirements are associated with lower earnings after displacement, and no evidence that changes in social or manual skills influence earnings losses around displacement.

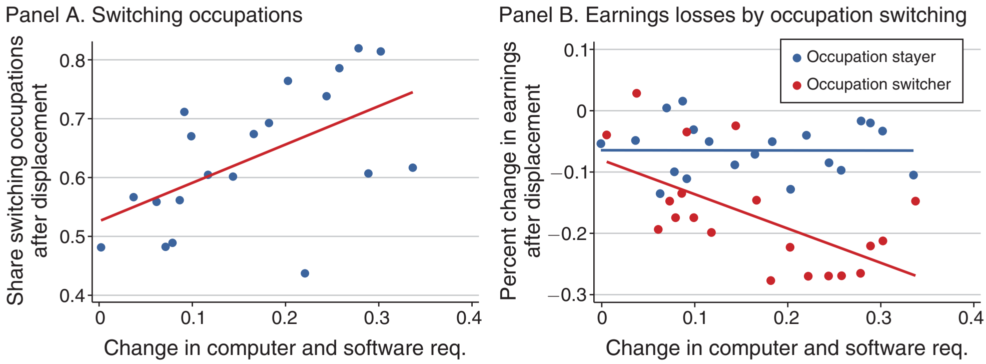


Figure 3. Technological Change and Occupation Switching, 2007–2017

*Notes:* Panel A presents a binned scatterplot of the probability of switching occupations after displacement ($y$-axis) by the change in the share of vacancies listing a computer or software requirement between 2007 and 2017 ($x$-axis). Panel B displays a binned scatterplot of earnings losses after displacement for occupation switchers (red line) and occupation stayers (blue line) ($y$-axis) by the change in the share of vacancies listing a computer or software requirement between 2007 and 2017 ($x$-axis). Occupations are measured using four-digit SOC codes.

Table 4—Technological Change and Occupation Switching

| Dependent variable: indicator for switching occupations | (1) | (2) | (3) |
|---|---|---|---|
| Change in computer requirements | 0.0847 | 0.0801 | 0.0682 |
| | (0.0269) | (0.0242) | (0.0171) |
| Change in employment share | | −0.0401 | −0.0274 |
| | | (0.0241) | (0.0177) |
| Observations | 6,742 | 6,742 | 6,742 |
| $R^2$ | 0.030 | 0.036 | 0.028 |
| Controls | Yes | Yes | Yes |
| Occupation definition | SOC-4 | SOC-4 | AD |

*Notes:* The table shows regression results from the estimation of equation (1), where the dependent variable is an indicator for switching occupations after displacement. Controls include the variables listed in the notes to Table 3. Clustered standard errors are in parentheses, where the clustering is performed at the occupation level. Columns 1 and 2 classify occupations by four-digit SOC code, while column 3 classifies occupations by Autor and Dorn (2013) occupation codes.

one standard deviation below the mean, the worker one standard deviation above the mean is nearly 17 percentage points more likely to switch occupations.

We next show the result that workers who are more exposed to new technologies are more likely to switch occupations is robust to additional controls and alternative classifications of occupations. In column 2 of Table 4 we control for the change in employment share in the occupation from which an individual was displaced. Incorporating the change in employment share controls for the changing demand for workers in an individual's original occupation. Including changes in employment share in the regression leaves our coefficient estimate on the change in computer and software requirements largely unchanged.[43] Additionally, we show that our results are robust to an alternative classification of occupations. In column 3, we measure occupation switching using the occupation classification of Autor and Dorn (2013). Using their occupation classification, we continue to find that workers who are more exposed to the introduction of new technologies are more likely to switch occupations. These results provide empirical support for Model Prediction 2 that workers who are more exposed to technological change are more likely to switch occupations after displacement.

We next examine Model Prediction 3 that the larger earnings losses of workers who are exposed to technological change are concentrated among occupation switchers. We first provide graphical evidence of this effect. Panel B of Figure 3 presents a binned scatterplot of changes in earnings after displacement for occupation switchers (red, dots and line) and occupation stayers (blue, dots and line) by the change in computer and software requirements in the occupation from which a worker was displaced. Consistent with Model Prediction 3, the figure shows that among occupation switchers there is a large negative effect of exposure to technological change on earnings losses following displacement. Conversely, for workers who are re-employed in their prior occupation, the size of earnings losses after displacement is not related to exposure to technological change.

We next formalize this finding in a regression framework. Let $S_{i,o,t}$ be a dummy variable equal to one if individual $i$, who is in the DWS in year $t$ and was displaced from occupation $o$, switches occupations following displacement. Let $\Delta\ln\left(Earn_{i,o,t}\right)$ denote the change in log real earnings of individual $i$, who is in the DWS in year $t$ and was displaced from occupation $o$. To test Model Prediction 3 that the larger earnings losses from exposure to technological change are concentrated among occupation switchers, we estimate the following regression:[44]

$$(2)\quad \Delta\ln\left(Earn_{i,o,t}\right) = \alpha + \gamma S_{i,o,t} + \beta\Delta\tilde{z}_o + \eta\left(\Delta\tilde{z}_o \times S_{i,o,t}\right) + \Gamma\mathbf{X}_{i,o,t} + \epsilon_{i,o,t}.$$

Table 5 presents the coefficient estimates of estimating equation (2). To further understand the role of exposure to technological change and occupation switching in contributing to earnings losses after displacement, we add the components of equation (2) sequentially. First, in column 1, we include the indicator for switching occupations after displacement. The coefficient on occupation switching indicates that switching occupations is associated with a decline in earnings that is over 9 percentage points larger compared to occupation stayers.[45] In column 2 of Table 5, we add the change in computer and software requirements to equation (2). We find that both occupation switching and exposure to technological change are associated with lower earnings after displacement.

[43] The negative coefficient on the change in employment share indicates that workers in expanding (contracting) occupations are less (more) likely to switch occupations following displacement. However, these coefficient estimates are only significant at the 10 percent level with the SOC-4 occupation classification and insignificant with the Autor and Dorn (2013) occupation classification.

[44] In addition to testing Model Prediction 3, this regression provides a statistical decomposition of the effect of exposure to technological change on earnings losses after displacement.

[45] The result that occupation switchers have larger earnings losses than occupation stayers is consistent with prior work by Stevens (1997); Kambourov and Manovskii (2009); and Huckfeldt (2022).

Table 5—Occupation Switching and Earnings Losses after Displacement

| Dependent variable: change in log earnings after displacement | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Occupation switch | −0.0912 | −0.0859 | −0.0175 | −0.0395 |
| | (0.0180) | (0.0182) | (0.0339) | (0.0245) |
| Change in computer requirements | | −0.0276 | 0.000532 | 0.00234 |
| | | (0.0124) | (0.0131) | (0.0105) |
| Change in computer requirements × occupation switch | | | −0.0494 | −0.0363 |
| | | | (0.0180) | (0.0158) |
| Observations | 6,742 | 6,742 | 6,742 | 6,742 |
| $R^2$ | 0.239 | 0.240 | 0.242 | 0.240 |
| Controls | Yes | Yes | Yes | Yes |
| Occupation definition | SOC-4 | SOC-4 | SOC-4 | AD |

*Notes:* The table shows regression results from the estimation of equation (2). Controls include the variables listed in the notes to Table 3 and the change in ACS employment share between 2007 and 2017 in the occupation from which an individual was displaced. Clustered standard errors are in parentheses, where the clustering is performed at the occupation level. Columns 1–3 classify occupations by four-digit SOC code, while column 4 classifies occupations by Autor and Dorn (2013) occupation codes.

Finally, in column 3 of Table 5, we incorporate the interaction between changes in computer and software requirements and occupation switching. Including the interaction between exposure to technological change and occupation switching changes the results in several important and illuminating ways. First, the coefficient on occupation switching is no longer statistically different from zero. This result then suggests that switching out of an occupation that is not exposed to technological change is not associated with lower earnings after displacement. Second, the coefficient estimate on the change in computer requirements indicates that the earnings of individuals who do not switch occupations following displacement are not affected by exposure to technological change. Third, the coefficient estimate on the interaction between changes in computer and software requirements and occupation switching is negative and statistically significant. The fact that the coefficient on the interaction term is negative and statistically significant indicates that the relationship between exposure to technological change and lower earnings following job loss is concentrated among occupation switchers. In column 4 of Table 5, we use the occupation classification from Autor and Dorn (2013) and find nearly identical results. The results presented in Table 5 provide empirical support for Model Prediction 3 that the larger earnings losses after displacement of workers who are more exposed to technological change are concentrated among occupation switchers.

The results in Table 5 indicate that individuals who are displaced from occupations that are undergoing greater technological change experience larger earnings losses, and that these earnings losses are concentrated among occupation switchers. Potentially, these individuals are switching occupations following job loss because they no longer have the skills to work in their original occupation. To test this hypothesis, we examine if, following displacement, workers who are more exposed to technological change are more likely to move to an occupation with lower computer and software requirements relative to their original occupation. In online Appendix C.3.1, we show that workers who are more exposed to technological change are in fact more likely to move to an occupation with lower computer and software requirements relative to their original occupation. These results suggest that individuals who switch occupations are doing so because they no longer have the skills to work in their prior occupation.[46]

The results presented in this section empirically support Model Predictions 2 and 3 and provide evidence that the mechanism through which technological change contributes to lower earnings following job loss works through occupation switching.[47]

### E. *Technological Change and the Probability of Displacement*

In this section, we examine how the likelihood of becoming displaced varies with the rate of technological change in an occupation. In the simple model in Section I, the probability of displacement is independent of exposure to technological change. Consistent with the structure of the model, we find that exposure to technological change does not affect the probability of displacement. Instead, changes in employment in an individual's occupation are associated with the probability of displacement.

We use equation (1) and the full sample of individuals who are in the DWS to examine how technological change affects the probability of being displaced.[48] Table 6 presents the results of estimating equation (1) where the dependent variable is an indicator for being displaced. The first column of Table 6 presents the results of estimating equation (1) without any controls. The coefficient shows that exposure to technological change is not statistically associated with changes in the probability of being displaced ($t$-statistic $= -0.39$). In addition to not being statistically significant, the coefficient is also not economically significant. Comparing a worker employed at one standard deviation above the mean change in computer and software requirements to a worker one standard deviation below the mean, we find that the worker one standard deviation above the mean is 0.25 percentage points less likely to be displaced. Relative to the mean displacement probability of nearly 6.7 percent, this is an economically small change in the displacement probability.

In column 2 of Table 6, we include the change in employment share by occupation between 2007 and 2017 as a control variable. As in column 1, changes in computer and software requirements are not associated with being more or less likely to become a displaced worker ($t$-statistic $= -0.30$). Conversely, changes in occupation employment share are associated with changes in displacement probability, with being employed in a declining (expanding) occupation associated with a higher (lower) probability of being displaced. When we compare a worker employed at one standard deviation above the mean change in employment share to a worker one

[46] In online Appendix C.3.2, we show that workers who are more exposed to technological change are more likely to transition to a lower-paying occupation after displacement. This result suggests that within-occupation technological change can induce workers to transition to lower-paying occupations. In prior work, Huckfeldt (2022) shows that earnings losses after displacement are concentrated among workers switching to lower-paying occupations.

[47] In online Appendix C.4, we show that exposure to technological change does not affect the length of an individual's unemployment spell in a statistically or economically significant manner. Hence, we do not find evidence that technological change lowers earnings through the length of unemployment or related duration dependence mechanisms.

[48] See online Appendix C.5 for details on the sample used in this estimation. In this online Appendix, we also provide graphical evidence for our result that exposure to technological change is not associated with changes in the probability of displacement.

Table 6—Technological Change and the Probability of Displacement

| Dependent variable: indicator for being a displaced worker | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Change in computer requirements | −0.00125 | −0.000891 | −0.000735 | −0.00401 | −0.00164 |
| | (0.00320) | (0.00293) | (0.00285) | (0.00266) | (0.00226) |
| Change in employment share | | −0.00946 | −0.00923 | −0.00854 | −0.00593 |
| | | (0.00363) | (0.00346) | (0.00283) | (0.00215) |
| Observations | 239,509 | 239,509 | 239,509 | 239,509 | 239,509 |
| $R^2$ | 0.000 | 0.001 | 0.010 | 0.012 | 0.012 |
| Year fixed effects | No | No | Yes | Yes | Yes |
| Controls | No | No | No | Yes | Yes |
| Occupation definition | SOC-4 | SOC-4 | SOC-4 | SOC-4 | AD |

*Notes:* The table shows regression results from the estimation of equation (1), where the dependent variable is an indicator for being a displaced worker. Controls include age, the level of computer requirements in 2007 in the worker's occupation, years of educational attainment, and gender fixed effects. Clustered standard errors are in parentheses, where the clustering is performed at the occupation level. Columns 1–4 classify occupations by four-digit SOC code, while column 5 classifies occupations by Autor and Dorn (2013) occupation codes.

standard deviation below the mean, we find that the worker one standard deviation above the mean is nearly 1.9 percentage points less likely to be displaced. Thus, the results from column 2 indicate that while exposure to technological change is not associated with changes in the probability of being displaced, changes in employment share in an individual's occupation are associated with changes in the probability of being displaced. Finally, we show that this result is robust to a series of additional controls (columns 3 and 4) and occupation classification (column 5).[49]

The results from Table 6 show that exposure to technological change is not associated with the probability of being displaced, a finding that is consistent with the structure of the simple model in Section I.[50] Conversely, the results show that being employed in an occupation with a declining employment share is associated with an increase in the probability of being displaced. Recall that the DWS aims to identify workers who have lost their job for exogenous reasons (e.g., their company or plant shut down, their shift or position was eliminated, or their firm had insufficient work). Our results suggest that the DWS is successful in identifying workers who've separated for exogenous reasons. In online Appendix C.9, we find a similar result for an earlier time period (1982–2000) that exposure to technological change is not associated with the probability of being displaced.

[49] In column 3 of Table 6, we incorporate survey year fixed effects to account for variation over time, and in column 4, we include additional controls for age, education, and gender as well as the level of computer and software requirements in 2007 in the individual's occupation. In column 5, we use the occupation classification from Autor and Dorn (2013).

[50] In online Appendix C.6, we show that exposure to technological change does affect a worker's ability to remain in an occupation. Using data from the CPS-ORG, we find that workers who are more exposed to technological change are more likely to switch occupations over a 12-month period. Our simple model predicts that this outcome occurs when workers who lack the necessary skills to match with newly created jobs in an occupation switch to another occupation where their skills are still employable, after an exogenous separation.

### F. *Gains from Technological Change*

In this section, we briefly examine the extent to which technological change benefits some workers. The theory in Section I builds from the premise that technological change increases the productivity and earnings of workers if they have the skills to use the new technology. We test this feature of the theory by examining how exposure to technological change affects the evolution of earnings among *occupation stayers*.

Using data from the CPS-ORG, we estimate equation (1) where the dependent variable is the change in log earnings over 12 months among occupation stayers. Table 7 presents the results.[51] We find that exposure to technological change increases earnings gains among occupation stayers. The positive and statistically significant coefficient on the change in computer requirements in column 1 of Table 7 indicates that occupation stayers who are more exposed to technological change experience larger earnings gains. Comparing a worker one standard deviation above the mean change in computer and software requirements to a worker one standard deviation below, we find that the worker one standard deviation above the mean has an increase in earnings that is over 0.5 percentage points higher.[52] The results presented in columns 2 and 3 show that this increase is robust to controlling for the change in employment share in an individual's occupation as well as using the occupation classification from Autor and Dorn (2013). This result highlights that exposure to technological change benefits some workers (e.g., occupation stayers) via larger earnings gains while simultaneously hurting other workers via larger earnings declines (e.g., displaced workers).[53]

### G. *Additional Results*

We conclude this section by briefly discussing a series of additional results.

*Broader Sample of Laid-Off Workers.*—In online Appendix E, we consider a broader sample of laid-off workers using a newly linked sample of SSA earnings records linked to the CPS Annual Social and Economic Supplement. In addition to considering a broader sample of laid-off workers, this analysis allows us to examine the path of earnings after layoff. We find that workers laid off from occupations that are more exposed to technological change have a persistently lower path of earnings after layoff and that this effect is concentrated among occupation switchers.

*Alternative Measures of Technological Change.*—We show that our results are robust to several alternative measures of technological change. First, in online Appendix C.7, we show that we find similar results using the change in computer requirements over time, as measured from O*NET. Second, we show in online Appendix C.8 that we

[51] See online Appendix C.6 for details on the CPS-ORG and sample construction. In Table 7, we require an individual to be an occupation stayer using both the SOC-4 and Autor and Dorn (2013) occupation classification.

[52] The average (median) increase in earnings among occupation stayers in the CPS-ORG is 1.58 percent (0.57 percent).

[53] In online Appendix C.6, we show that workers in the CPS-ORG that are more exposed to technological change are more likely to switch occupations.

Table 7—Technological Change and Earnings Gains among Occupation Stayers

| Dependent variable: change in log earnings over 12 months | (1) | (2) | (3) |
|---|---|---|---|
| Change in computer requirements | 0.00270 | 0.00272 | 0.00205 |
| | (0.000705) | (0.000680) | (0.000804) |
| Change in employment share | | 8.76e-05 | 0.000145 |
| | | (0.000595) | (0.000598) |
| Observations | 150,330 | 150,330 | 150,330 |
| $R^2$ | 0.005 | 0.005 | 0.005 |
| Controls | Yes | Yes | Yes |
| Occupation definition | SOC-4 | SOC-4 | AD |

*Notes:* The table shows regression results from the estimation of equation (1) using data from the CPS-ORG, where the dependent variable is the change in log earnings over a 12-month period among occupation stayers. Controls include year fixed effects, gender fixed effects, as well as controls for age, years of completed education, and the initial level of computer requirements in 2007. Clustered standard errors are in parentheses, where the clustering is performed at the occupation level. Columns 1 and 2 classify occupations by four-digit SOC code, while column 3 classifies occupations by Autor and Dorn (2013) occupation codes.

find similar results using an alternative timing assumption about the changes in computer and software requirements, as measured in the Burning Glass data. Finally, in online Appendix C.9, we show that we obtain similar results for an earlier time period (1982–2000) using a measure of technological change based on skill requirements in newspaper job ads collected by Atalay et al. (2020).

*Employment and Out of Labor Force.*—Finally, we examine the impact of technological change on other outcomes for displaced workers. In online Appendix C.10, we show that exposure to technological change *does not* affect the probability of regaining employment after displacement or the probability of exiting the labor force.

## V. Quantitative Model

The results of the previous section provided empirical support for the model predictions from Section I by showing that displaced workers who are more exposed to technological change suffer larger earnings losses and that the effect is concentrated among occupation switchers. In this section, we extend and quantify the simple model from Section I. We use the quantitative model as a laboratory in which to decompose the source of earnings losses after job loss and measure the share of earnings losses that are accounted for by technological change.

### A. *Model Overview*

In this section, we give an overview of the quantitative model. Time is discrete and runs forever. There is a unit measure of workers and a continuum of potential entrant firms. Let $z_j$ denote the level of technology at time $j$. We assume the level of technology grows at a constant rate $g > 0$ over time.

In the labor market, there are $K \geq 2$ occupations, or islands in the spirit of Lucas and Prescott (1974). Occupations differ in the level of technology that they use in production. 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 $z_{k,j} = c_k z_j$. The heterogeneity in occupations, where some occupations employ a greater amount of technology in production (and pay a high wage) while other occupations use lower levels of technology (and pay a lower wage), is similar to the vertical ranking of occupations documented in Groes, Kircher, and Manovskii (2015).

Potential entrant firms pay an entry cost $\kappa_j$ to post a vacancy at time $j$ and choose which occupation $k \in \mathcal{K}$ to post a vacancy in, subject to a free-entry condition. Vacancies that go unfilled exit the labor market. Workers direct their search across occupations (e.g., Lucas and Prescott 1974 and Wiczer 2015). Once a match is formed, the level of technology in the match is fixed for the duration of the match. This form of technological change is *embodied* in matches, as in Mortensen and Pissarides (1998); Violante (2002); Postel-Vinay (2002); and Eyigungor (2010). In order for a worker to become employed with a newer vintage of technology, the worker must match with a new vacancy either through on-the-job search or after a spell of unemployment.

There are $T$ overlapping generations of workers, as in Menzio, Telyukova, and Visschers (2016). Workers live $T$ periods. Workers are either employed ($e = W$) or unemployed ($e = U$) and search for a job when both employed and unemployed. Workers direct their search for jobs across occupations $k \in \mathcal{K}$ and wage piece rates $\omega \in [0,1]$, which specify the share of per-period output that the worker receives as a wage.

Workers are heterogeneous in their human capital (or skills), which is denoted by $h \in \mathcal{H} \equiv [\underline{h}, \bar{h}]$. Workers are also either inexperienced ($x = N$) or experienced ($x = E$) in their current occupation $k$. Workers become experienced with probability $\lambda_E$ when they remain employed in an occupation $k$. Becoming experienced raises a worker's production and wages in an occupation by a factor $A_E > 1$. When experienced workers are unemployed, they become inexperienced with probability $\lambda_N$. Additionally, experienced workers become inexperienced by accepting a job in a new occupation. Human capital $h$ can be thought of as general human capital, while experience $x$ can be thought of as occupation-specific human capital.[54]

Workers are risk neutral and discount the future at rate $\beta \in (0,1)$. New workers enter as inexperienced unemployed workers and draw their human capital from a distribution $\Gamma_j(h): \mathcal{H} \rightarrow [0,1]$.

In the labor market, workers direct their search for jobs across occupations and wage piece rates both while employed and while 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 $s$.[55] Since search is directed, there is a separate labor market tightness for each submarket, defined by the time period $j$, and the occupation of the firm $k$, as well as the wage piece rate $\omega$, worker's age $t$, human capital $h$, and experience $x$. In each submarket, the job-finding rate for individuals, $p(\cdot)$, is a function of the labor market tightness $\theta_{j,t}^x(h,k,\omega)$,

[54] Modeling the acquisition of occupation-specific human capital as a stochastic process from being inexperienced to experienced follows Kambourov and Manovskii (2009). Workers losing their occupation-specific human capital stochastically while being unemployed is similar to the notion of turbulence presented in Den Haan, Haefke, and Ramey (2001) and Fujita (2018).

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

such that $p\left(\theta_{j,t}^{x}(h,k,\omega)\right) = \frac{M\left(s_{j,t}^{x}(h,k,\omega), v_{j,t}^{x}(h,k,\omega)\right)}{s_{j,t}^{x}(h,k,\omega)}$. The hiring rate for firms $p_f(\cdot)$ is also a function of labor market tightness and is given by $p_f\left(\theta_{j,t}^{x}(h,k,\omega)\right) = \frac{M\left(s_{j,t}^{x}(h,k,\omega), v_{j,t}^{x}(h,k,\omega)\right)}{v_{j,t}^{x}(h,k,\omega)}$. Workers are displaced exogenously each period with probability $\delta$. Agents receive a public insurance transfer $b_j > 0$ from the government if unemployed at time $j$.[56]

When workers with human capital $h$ and experience $x$ match with a firm in occupation $k$ at time $j$, they produce $f\left(c_k z_j, h, x\right)$. We use an "up-to-the-task" production function (e.g., Albrecht and Vroman 2002 and Jarosch and Pilossoph 2019), which requires that workers have a minimum amount of human capital to produce with a given level of technology. We use the up-to-the-task production function because it introduces a notion of skill requirements to work in a given occupation.

In equilibrium, the cost of posting a vacancy $\kappa_j$, the value of public insurance transfers $b_j$, 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 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 $\mu = 1/(1+g)$. In the estimation, we model the depreciation of match technology $(z)$ and human capital $(h)$ as occurring stochastically so that they depreciate by factor $\mu$, on average, over a model year.

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, production and wage payments occur.

The aggregate state of the economy is given by $\Omega(e,h,x,k,\omega,z) \rightarrow [0,1]$, which is a distribution of workers across employment status $(e)$, human capital $(h)$, experience $(x)$, occupations $(k)$, wage piece rates $(\omega)$, and vintages of technology $(z)$. 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.

## B. *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.

Let $U_t^N(h,0)$ denote the value of being an inexperienced, unemployed worker of age $t$ and human capital $h$. In the current period, the unemployed worker receives the transfer from the government $b$. At the start of the next period after shocks to human capital are realized, the unemployed worker searches for a job in the inexperienced

[56] For ease of exposition, the public insurance transfer $b_j$ is financed outside of the model. The results are virtually unchanged if the public insurance transfers are funded through a proportional labor income tax that is levied on all employed workers.

labor market by searching across the set of occupations as well as wage piece rates and applies for a job with the highest continuation value. The value to an inexperienced, unemployed worker is

$$U_t^N(h,0) = b + \beta E\left[\hat{U}_{t+1}^N(h',0)\right], \ \forall t \leq T,$$

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

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

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

and the law of motion for a worker's human capital,

$$h' = H(h).$$

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. Online Appendix D.1 contains the Bellman equation for experienced, unemployed workers.

Let $W_t^N(h,z,k,\omega)$ denote the value of being an inexperienced worker with human capital $h$, who is employed at a firm in occupation $k$ that uses technology $z \leq \bar{z}$ and receives share $\omega$ of the match output as a wage. In the current period, the agent receives wages from the match. At the start of the next period, shocks to human capital and match technology are realized, and the worker becomes unemployed with probability $\delta$. Workers who become unemployed are immediately allowed to search in the labor market. If the worker is not hit by the separation shock $\delta$, then the worker becomes experienced in occupation $k$ with probability $\lambda_E$. 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 search for a job in their own occupation in the experienced labor market and search for a job in all other occupations in the inexperienced labor market. If the worker did not become experienced, then they search in the inexperienced labor market for all occupations. The continuation value of the inexperienced, employed worker is

$$W_t^N(h,z,k,\omega) = \omega f(c_k z,h,N) + \beta E\left\{\delta \hat{U}_{t+1}^N(h',k) + (1-\delta)\left[\lambda_E \hat{W}_{k,t+1}^E(h',z',k,\omega) + (1-\lambda_E) \times \hat{W}_{t+1}^N(h',z',k,\omega)\right]\right\}, \forall t \leq T,$$

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

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

$$\begin{aligned}\hat{W}^N_{t+1}(h', z', k, \omega) \;=\; & \max_{(\tilde{k},\tilde{\omega})\in\mathcal{K}\times[0,1]} p\left(\theta^N_{t+1}(h', \tilde{k}, \tilde{\omega})\right) W^N_{t+1}(h', \bar{z}, \tilde{k}, \tilde{\omega}) \\ & + \left[1 - p\left(\theta^N_{t+1}(h', \tilde{k}, \tilde{\omega})\right)\right] W^N_{t+1}(h', z', k, \omega),\end{aligned}$$

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

$$\begin{aligned}\hat{W}^E_{t+1}(h', z', k, \omega) \;=\; \max\Bigg\{ & \max_{\tilde{\omega}\in[0,1]} p\left(\theta^E_{t+1}(h', k, \tilde{\omega})\right) W^E_{t+1}(h', \bar{z}, k, \tilde{\omega}) \\ & + \left[1 - p\left(\theta^E_{t+1}(h', k, \tilde{\omega})\right)\right] W^E_{t+1}(h', z', k, \omega), \\ & \max_{(\tilde{k},\tilde{\omega})\in\mathcal{K}/\{k\}\times[0,1]} p\left(\theta^N_{t+1}(h', \tilde{k}, \tilde{\omega})\right) W^N_{t+1}(h', \bar{z}, \tilde{k}, \tilde{\omega}) \\ & \times \left[1 - p\left(\theta^N_{t+1}(h', \tilde{k}, \tilde{\omega})\right)\right] W^E_{t+1}(h', z', k, \omega) \Bigg\},\end{aligned}$$

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

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

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

To conclude this section, we briefly discuss how we close the economy. In the model, firms post vacancies subject to a free-entry condition. In online Appendix D.3, we present the Bellman equations that govern the behavior of firms in the economy. Finally, in online Appendix D.4, we present the definition of a recursive competitive equilibrium for the quantitative model.

## C. *Calibration*

In this section, we discuss how we take the model to the data.[57] The model is estimated at a quarterly frequency, and we calibrate the model to the 2010–2017 time period to abstract from the impacts of the Great Recession. We use the increase in the share of vacancies listing computer or software requirements to set the growth rate of technology $g$, which averages 1.5 percent per year over this time period.[58] We normalize the value of the frontier technology to 1 (i.e., $\bar{z} \;=\; 1$) and then assign

[57] In online Appendix D.5, we present the algorithm for solving the quantitative model.

[58] Between 2010 and 2017, the share of vacancies listing computer or software requirements increased from 26.67 percent of vacancies to 29.67 percent. These estimates are weighted using the ACS employment shares between 2010 and 2017.

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 $g = 1.5$ percent.[59] All matches between workers and firms start at the frontier technology $(\bar{z})$ and then evolve according to the following stochastic process:

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

where $\mu = 1/(1 + g)$ 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 $\iota = 0.25$.

In the labor market, we set the job destruction rate to 10 percent per quarter, $\delta = 0.10$ (Shimer 2005). Matching in the labor market is defined using a constant returns to scale matching function that yields well-defined job-finding probabilities:

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

The matching elasticity parameter is chosen to be $\xi = 1.6$, as estimated in Schaal (2017). The entry cost of posting a vacancy $\kappa$ is estimated by targeting an unemployment rate of 6.8 percent, which is the average reported by the Bureau of Labor Statistics from 2010 to 2017.

When workers and firms match with one another, 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

$$f(c_k z, h, x) = \begin{cases} A_x c_k z, & \text{if } A_x h \geq c_k z; \\ 0, & \text{otherwise;} \end{cases}$$

where the parameter $A_x$ denotes the relative productivity of workers with experience $x \in \{E, N\}$.[60] We normalize the relative productivity of inexperienced workers to 1 (i.e., $A_N = 1$). Following the estimates on the returns to occupation tenure from Kambourov and Manovskii (2009), we set the relative productivity of experienced workers to $A_E = 1.12$, which generates a 12 percent increase in productivity and wages for experienced workers. Workers become experienced (on average) after being in an occupation for five years. Given the quarterly timing of the model, we set the probability of becoming experienced to $\lambda_E = 0.05$. When workers are unemployed, they become inexperienced with probability $\lambda_N$. We calibrate the probability of becoming inexperienced while unemployed to match the share of individuals who switch occupations after layoff. For workers displaced between 2010 and 2017, we find that 62 percent switch occupations following job loss.

[59] We use a grid with seven grid points where $\mathcal{Z} = [0.9145, 1]$. Increasing the number of grid points on the technology grid (which would add points to the bottom of the grid) does not alter the results, as virtually all workers in a match exit the match before the match hits the bottom level of the technology grid.

[60] This production function imposes the restriction that workers with low levels of skills (measured via both their general and their occupation-specific human capital) are unable to work in occupations with high levels of technology. As commented in Jarosch and Pilossoph (2019), the "up-to-the-task" production function is consistent with estimates by Lise and Robin (2017), who estimate a flexible production function and find that low-skill workers have limited ability to match with highly productive firms.

Workers' general human capital ($h$) also evolves while in the labor market. The grid on human capital $\mathcal{H}$ 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 $g = 1.5$ percent. The general human capital of individuals evolves according to

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

Unemployed agents receive public insurance transfers from the government ($b$). 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. Using the Panel Study of Income Dynamics from the period 2001 to 2013, Braxton, Herkenhoff, and Phillips (2020) estimate that public insurance to the unemployed replaces 41.2 percent of lost earnings.

We next discuss the mapping between occupations in the data and the model. In the empirical analysis of Section III, our primary notion of an occupation was a four-digit SOC code, which classifies over 100 unique occupations. For tractability in the quantitative model, we consider $K = 10$ occupations.[61] To map occupations in the data to occupations in the model, we group together occupations with similar computer and software requirements.[62] To obtain the technology intensity in each occupation ($\{c_k\}_{k=1}^{k=10}$), we use variation in earnings across the ten occupation groups. Given the production function and wage process specified above, the technology intensity of an occupation governs the level of the wage in that occupation, and occupations with higher levels of technology pay higher wages, holding all else fixed. Let $\bar{e}_k$ denote smoothed earnings in occupation $k$.[63] 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. Using the CPS-ORG, we measure this ratio to be 0.775. 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 $\left(\bar{e}_k/\bar{e}_1\right)$.

A worker's life span is set to $T = 120$ quarters (30 years). Newly born agents enter the model as unemployed, inexperienced workers. Newly born agents draw their initial human capital from an inverted exponential distribution with parameter $\lambda_H$, which is calibrated to match the difference in the seventy-fifth and twenty-fifth percentile log earnings residuals among individuals with less than five years of potential experience from a regression of log earnings on experience.[64] Agents have risk-neutral preferences, and we set the quarterly discount rate for workers to $\beta = 0.99$.

Table A21 in online Appendix D.6.1 contains a summary of the model parameters, and Table A22 displays the calibrated parameters and their calibration targets. The

[61] In online Appendix D.7, we show that the predictions of the quantitative model and the decomposition exercise in Section VE are robust to using a greater number of occupations.

[62] In online Appendix D.6.2, we show the cutoffs used to generate the ten occupation groups.

[63] We generated smoothed earnings by averaging the predicted values from a regression of computer and software requirements in 2010 on individuals' earnings in the occupation in which they are employed. In online Appendix D.6.2, we present the details for our estimation of the smoothed earnings and the process for calibrating $c_k$.

[64] 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.

estimated model matches the targeted moments very well. We discuss nontargeted moments in the next subsection.

### D. *Model Impact of Technological Change on Displaced Workers*

In this section, we analyze the model's predictions on the role of technological change on the outcomes of displaced workers. In the model, occupations are heterogeneous in their technology intensity $c_k$. For a given change in the frontier technology $\Delta z$, occupations with greater technology intensity experience a larger increase in the human capital (skill) requirements necessary to work in that occupation.[65] We estimate the outcomes of displaced workers by the change in technology (skill requirements) in the occupation from which they were displaced and discuss how these estimates compare to the estimates from the data presented in Section IV.[66] These moments were not targeted in the calibration and serve as a model validation exercise.

To compare estimates from the model to the data, we sample agents in the model two years after job loss to align with the observation that, on average, individuals in the DWS are two years after job loss. For each model agent, we record their occupation and earnings in the quarter prior to displacement and two years after being displaced. Based on a model agent's occupation prior to displacement, we form quintiles of displaced workers based on the change in technology in their occupation (i.e., the technology intensity $(c_k)$ of their occupation).[67] We then measure the change in earnings, as well as the change in earnings by occupation switchers and stayers across these quintiles, and compare these measures to the data.

Panel A of Figure 4 shows the average change in earnings following displacement by quintile 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 nearly 9 percent of predisplacement earnings. Conversely, workers in the first quintile experience the smallest decline in earnings of just over 2 percent of predisplacement earnings. These patterns are qualitatively consistent with the estimates from the data, which show that individuals displaced from occupations that are more exposed to technological change 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 4 shows the change in earnings by technological change quintile for individuals who switch occupations

[65] Recall that the production function is such that a worker's human capital must exceed the technology used in production to be able to produce in a given occupation.

[66] The data estimates in this section use 2010–2017 data to align with the time period of the calibrated model.

[67] As discussed above, occupations with higher technology intensity $c_k$ experience a greater change in technology (skill requirements).

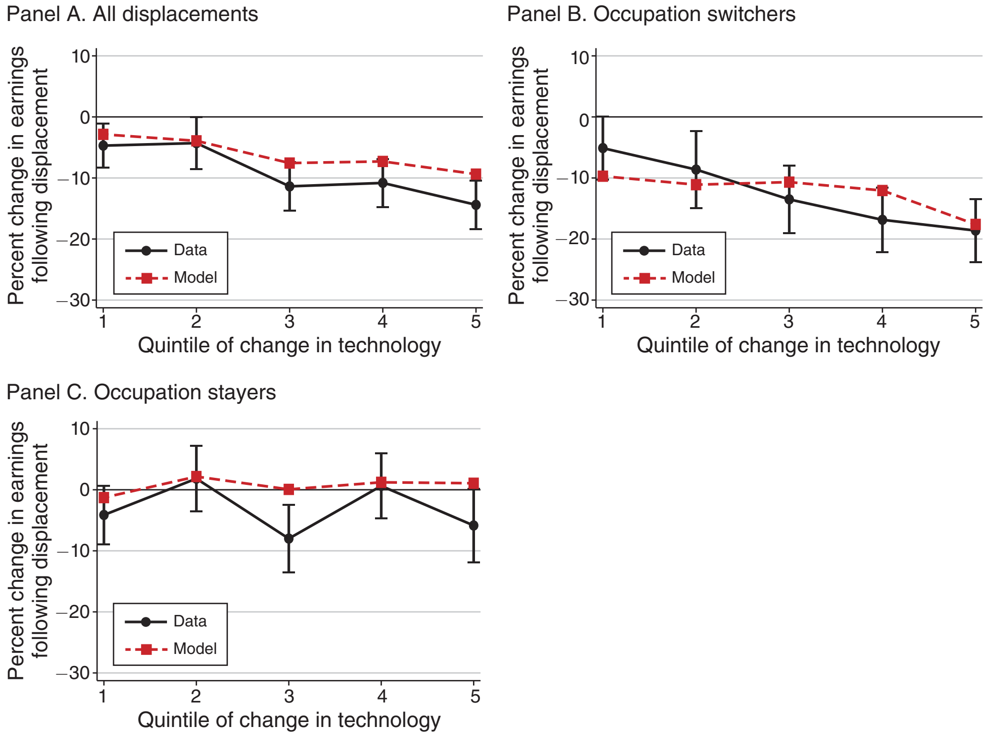


FIGURE 4. NONTARGETED MODEL MOMENTS: CHANGES IN EARNINGS AFTER DISPLACEMENT

*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 percent confidence intervals of data estimates.

following job loss, and 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 stayers, 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 in this section show that the calibrated model qualitatively captures the empirical patterns documented in Section IV. 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. In the next section, we decompose the decline in earnings to estimate the share of the decline due to technological change.

### E. *Decomposing Earnings Losses after Displacement*

In this section, we use the model to decompose the sources of earnings losses after displacement. In particular, we examine the role of technological change, occupation-specific human capital, and moving to a lower position on the job ladder in generating earnings losses after displacement. To measure the relative importance of these channels, we remove each feature of the model sequentially and measure the average size of earnings losses generated by the model. We find that technological change accounts for over 45 percent of the decline in earnings after job loss, while the loss of occupation-specific human capital and moving lower on the job ladder account for approximately 35 percent and 20 percent, respectively.

We start by removing technological change from the model, which requires setting the technology growth rate to zero (i.e., $g = 0$).[68] As in Section VD, we measure earnings losses in the model two years after job loss and restrict our sample to agents who have regained employment. In the model without technological change, the average decline in earnings is 4.16 percent. In the baseline model, the average decline in earnings is 7.63 percent. Hence, technological change accounts for 45.5 percent of the decline in earnings following job loss in the baseline model.

We next remove occupation-specific human capital (experience) from the model (i.e., $A_E = A_N = 1$). In the model without technological change and occupation-specific human capital, earnings are 1.53 percent lower after layoff. This decomposition reveals that occupation-specific human capital accounts for 34.5 percent of the decline in earnings following job loss. In the model without technological change or occupation specific human capital, the remaining decline in earnings after job loss of 1.53 percent is attributable to being at a firm with a lower wage piece rate (i.e., moving to a lower position on the job ladder). Hence, moving to a lower position on the job ladder accounts for 20 percent of the decline in earnings after job loss. Figure 5 summarizes the results of the decomposition exercise.

The results in this section show that technological change accounts for over 45 percent of the decline in earnings following job loss. Loss of occupation-specific human capital and moving to a lower position on the job ladder account for the remaining decline in earnings following job loss. Technological change generates earnings losses after job loss as workers fall behind the technological frontier for their occupation and no longer have the skills to work in their prior occupation.

## VI. Conclusion

In this paper, we examine the cause of the large and persistent decline in earnings following job loss. We find that technological change, as measured through changes in computer and software requirements, plays a significant role in the earnings losses of displaced workers. Empirically, we document that workers displaced from occupations that are more exposed to technological change (i) experience a larger decline in earnings and (ii) are more likely to switch occupations. Further, we show that the larger earnings losses among workers who are more exposed to

[68] Online Appendix D.6.3 discusses the estimation of the model without technological change.

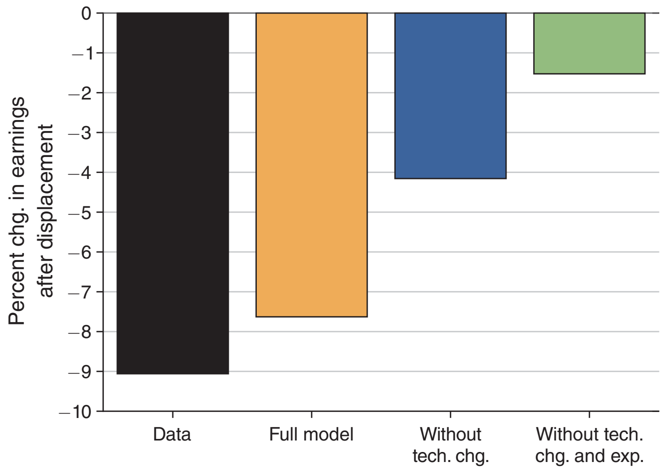


FIGURE 5. DECOMPOSING EARNINGS LOSSES AFTER DISPLACEMENT

*Notes:* The figure shows the percent change in earnings after displacement in the data as well as in different estimations of the model. The black bar measures the average size of earnings losses in the data. The orange bar measures the average size of earnings losses in the full model. The blue bar measures the average size of earnings losses in the model without technological change. Finally, the green bar measures the average size of earnings losses in the model without technological change and occupation-specific human capital (experience). In all cases, individuals have regained employment.

technological change occur among occupation switchers. We then quantify the theory in a model of the labor market that integrates technological change, occupation choice, and employment risk. The model is able to replicate the empirical facts documented in this paper. Using the quantitative model, we find that technological change accounts for over 45 percent of the decline in earnings following job loss.

These results suggest that a large share of the decline in earnings after job loss is accounted for by workers who no longer having the skills to work in their prior occupations. This finding suggests that policies that encourage retaining during unemployment may play a role as part of the optimal policy for unemployed workers. In Braxton and Taska (2022), we are examining the optimal use of retraining subsidies in conjunction with unemployment insurance using an extended version of the quantitative model from this paper. Further, the Burning Glass data used in this paper can help illuminate the types of skills where retraining may be appropriate and how this varies across occupations.

Our empirical results also demonstrate that technological change is a common force that generates larger earnings gains for some workers (e.g., occupation stayers) but larger earnings losses for other workers (e.g., displaced workers). We view this dichotomy as an important point for thinking about policies that influence technological change, as policies which aim to promote technological change (e.g., R&D subsidies) may have the unintended consequence of making earnings losses for displaced workers more severe.

Additionally, the mechanism highlighted in this paper that greater exposure to technological change generates larger earnings losses after displacement suggests a potential link between two recently documented facts: (i) earnings losses are more severe in recessions (e.g., Davis and von Wachter 2011) and (ii) technological change accelerates during recessions (e.g., Hershbein and Kahn 2018, and Jaimovich and Siu 2020). Hence, the larger earnings losses that occur in recessions are potentially due to the acceleration in technological change during these time periods.[69] In future work, we plan to further explore this phenomenon as well as its implications for earnings dynamics over the business cycle.

Finally, we view this paper as part of an emerging research agenda that aims to open the "black box" of earnings dynamics. A key part of this agenda is creating new, richer datasets that link administrative records to surveys as well as databases created by the private sector. The creation of these datasets allow researchers to more fully examine the factors that cause an individual's earnings to evolve over both short and long horizons. A recent example of this work is Braxton et al. (2021), who link SSA earnings records to CPS responses with the aim to more broadly examine income fluctuations and how they have evolved over time.

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[69] Consistent with this mechanism, Huckfeldt (2022) shows that occupation switching after displacement increases in recessions.

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