Online Appendix - Technological Change and the Consequences of Job Loss*

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A Simple model: additional details

In this appendix, we characterize the predictions of the simple two-period model of the labor market with technological change introduced in Section I. We first characterize the cutoff rule for occupation search. We then characterize the predictions of the model for the impact of technological change on the outcomes of displaced workers.

Occupation search cutoff rule. In this section, we prove the existence of the search cutoff rule in the two-period model where occupation search decisions are given by the rule: (1) if $h \geq z_H$, then the agent applies for a job in the high-technology occupation (z_H) and (2) if $h < z_H$ then the agent applies for a job in the low-technology occupation (z_L). For ease of exposition, we prove the cutoff rule in the case where there is no technological change in the second period. The proof with the introduction of the new technology follows naturally. Additionally, for ease of exposition and because of our focus on the outcomes of displaced workers, we assume there is no on-the-job search.[1]

First, we consider the search problem of an unemployed worker in the second period. Let $U_2(h)$ denote the value to searching as an unemployed worker in the second period for a worker with human capital h. The unemployed worker directs their search over occupations $z \in \{z_L, z_H\}$ and applies for a job in the occupation, which maximizes their continuation value. With probability $p(h,z)$ the worker matches with the job for which they applied. For ease of exposition, we have assumed that $p(h,z) = 1$ if $h \geq z$, and is equal to zero otherwise. If the worker matches with a job in occupation z, then the worker receives ωz as a wage. Alternatively, if the worker does not match they receive a transfer b, where we assume that $b < \omega z_L$, i.e., the value of the transfer is lower than the wage in the low-technology occupation. The value to searching in the second period is then given by,

$$U_2(h) = \max_{z \in \{z_L, z_H\}} p(h,z)\omega z + (1 - p(h,z))b$$

We next characterize the occupation search decision of an agent. First consider a worker with human capital such that $h < z_H$. Since $\omega z_L > b$, we have that for workers with $h < z_H$, they will apply for a job in the low-technology occupation (z_L). Next consider a worker with human capital such that $h \geq z_H$. Since $\omega z_H > \omega z_L$, we have that the worker will apply for a

[1] In the case of no technological change there will not be a motive for on-the-job search. With technological change, on-the-job search also follows a cutoff rule where if $h \geq z_H^{'}$ agents will engage in on-the-job search to transition to the new matches which use the new technology in production and pay a higher wage. All other workers would remain in their current match.

job in the high-technology occupation. Based upon these search decisions, the value to search in the second period can be written as:

$$U_2(h) = \begin{cases} \omega z_H & \text{if } h \geq z_H \\ \omega z_L & \text{if } h < z_H \end{cases}$$

Next, we consider the search problem for an unemployed agent in the first period.[2] Let $U_1(h)$ denote the value to searching as an unemployed worker in the first period for a worker with human capital h. The worker directs their search across occupations $z \in \{z_L, z_H\}$ and applies for a job in the occupation which maximizes their continuation value. If the worker matches in occupation z, then in the current period they receive wage ωz. At the end of the period with probability δ the match ends. If the match continues, then the worker receives wage ωz in the second period. If the match ends, then the worker searches in the labor market in the second period as an unemployed worker as detailed above. Alternatively, if the worker does not match in the first period, they receive the transfer b and in the second period search in the labor market as an unemployed worker. The value of search in the first period is given by,

$$U_1(h) = \max_{z \in \{z_L, z_H\}} p(h,z)\left[\omega z + (1-\delta)\beta\omega z + \beta\delta U_2(h)\right] + (1 - p(h,z))\left[b + \beta U_2(h)\right]$$

We now characterize the occupation search decision of an agent in the first period. First, consider a worker with human capital such that $h < z_H$. If the worker applies for a job in the high-technology occupation they receive value $b + \beta\omega z_L$, while if they apply for a job in the low-technology occupation they receive payoff $\omega z_L + \beta\omega z_L$. Since $\omega z_L > b$, the worker searches in the low-technology occupation. Finally, consider a worker with human capital $h \geq z_H$. If the worker applies for a job in the low-technology occupation they receive payoff $\omega z_L + \beta(1-\delta)\omega z_L + \beta\delta\omega z_H$, while if they apply for a job in the high-technology occupation they receive payoff $\omega z_H + \beta(1-\delta)\omega z_H + \delta\beta\omega z_H$. Since $\omega z_H > \omega z_L$, the worker searches in the high technology occupation.

Thus, we have established that in the simple two-period model a worker's occupation search is performed via a cutoff rule where: (1) if $h \geq z_H$ then the worker applies for a job in the high-technology occupation (z_H) and (2) if $h < z_H$ then the worker applies for a job in the low-technology occupation (z_L).

Finally, we comment on the search decision in the second period after the introduction of the new technology. Following the same steps as above, the occupation search decision of an

[2] Recall that all agents enter into the model as unemployed in the first period.

unemployed worker in the second period follows a cutoff rule where (1) if $h \geq z_H^{'}$ then the worker applies for a job in the high-technology occupation and (2) if $h < z_H^{'}$ then the worker applies for a job in the low-technology occupation.

Using these occupation search decisions, we can now characterize the predictions for the model on the implications of technological change for the outcomes of displaced workers.

Model Prediction 1: Earnings losses.

- **Model Prediction 1:** If $\pi > \frac{\gamma}{\eta+\gamma}$, then workers displaced from the occupation that introduced the new technology experience larger earnings losses, on average, than workers from the occupation with no change in technology.

We show this result by considering earnings losses for workers displaced for each occupation.

In the low tech occupation before displacement workers make ωz_L and after displacement they make ωz_L, so there are no earnings losses.

In the high tech occupation, before displacement workers make ωz_H, and after displacement occupation switchers make ωz_L while occupation stayers make $\omega z_H^{'}$. Given the occupation search decisions defined by the cutoff rule above, $\pi = \frac{F(z_H^{'})-F(z_H)}{1-F(z_H)}$ denotes the share of workers who were employed in the high-technology occupation who switch occupations after displacement, where $F(h)$ is the CDF of general human capital h. For workers displaced from the occupation which introduced the new technology, average earnings after displacement are: $\pi\omega z_L + (1-\pi)\omega z_H^{'}$. We then have that if $\pi > \frac{\gamma}{\eta+\gamma}$, then there is an average earnings loss for workers from the occupation that introduced the new technology. Since there are no earnings losses in the occupation that did not introduce a new technology, the model predicts that exposure to technological change generates larger earnings losses following displacement.

Model Prediction 2: Occupation switching.

- **Model Prediction 2:** Workers displaced from the occupation that introduction the new technology are more likely to switch occupations following displacement (i.e., $\pi > 0$).

As discussed above, given the cutoff rule for occupation search, share π of workers employed in the high-technology occupation in the initial steady state switch occupations after displacement. Conversely, no workers in the low-technology occupation switch occupations after displacement. Hence, exposure to technological change raises the probability of switching occupations after displacement.

Model Prediction 3: Role of occupation switching.

- **Model Prediction 3:** The larger earnings losses for workers displaced from the occupation that introduced the new technology occurs among the occupation switchers .

As discussed above, the decline in earnings for workers exposed to technological change occurs among workers who switch out of the high-technology occupation and move to the low-technology occupation.

B Additional results: measure of technological change

In this appendix, we provide additional results on our measure of technological change based upon changes in computer and software requirements reported in the Burning Glass database.

B.1 Change in computer and software requirements by 2-digit SOC

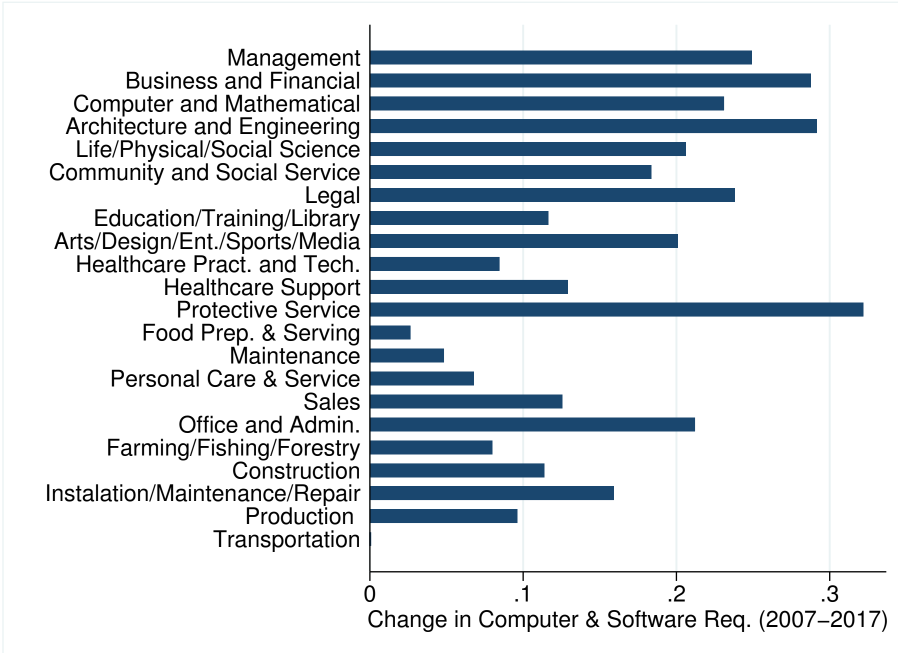
Figure A1 plots the change in computer and software requirements by two-digit SOC codes. The figure shows that all two-digit occupations experienced an increase in computer and software requirements between 2007 and 2017. However, there is noticeable heterogeneity across occupations. The two-digit occupations with the largest increase in computer and software requirements include: protective services, architecture and engineering, as well as business and finance. The occupations with the smallest increases in computer and software requirements include transportation, food preparation and service, maintenance, as well as personal care and service.

B.2 Additional results: which occupations are changing computer and software requirements?

In this appendix we provide some additional results and figures on which occupations are changing computer and software requirements over time.

In Figure A2 we present binned scatter plots of the change in computer and software requirements by measures of the task content of an occupation. In each binned scatter, on the x-axis we place occupations into ventiles based upon the measure of task content in question (e.g., non-routine cognitive, routine cognitive, etc.) and on the y-axis plot the average change in computer and software requirements within the ventile. We measure the task content of an occupation using the measures from Acemoglu and Autor (2011). Each measure is normalized to be mean zero and have unit variance, with higher values of the index indicating the occupation

Figure A1: Changes in computer and software requirements by occupation



Note: The histogram shows the changes in computer and software requirements as measured in the Burning Glass data between 2007 and 2017 by two-digit SOC code.

has a greater share of the specific form of task content. Figure A2 presents the results. Panel (a) of Figure A2 shows that occupations which have greater non-routine cognitive task content have experienced a larger increase in computer and software requirements over time. Similarly, panel (b) of Figure A2 shows that occupations which have greater routine cognitive task content have undergone a larger increase in computer and software requirements over time. Conversely, panels (c) and (d) of Figure A2 show that occupations which are higher in non-routine manual task content and routine manual task content have seen smaller increases in computer and software requirements over time. The results of Figure A2 indicate that occupations with large increases in computer and software requirements tend to be cognitive occupations, while occupations with smaller increases in computer and software requirements tend to be manual occupations.

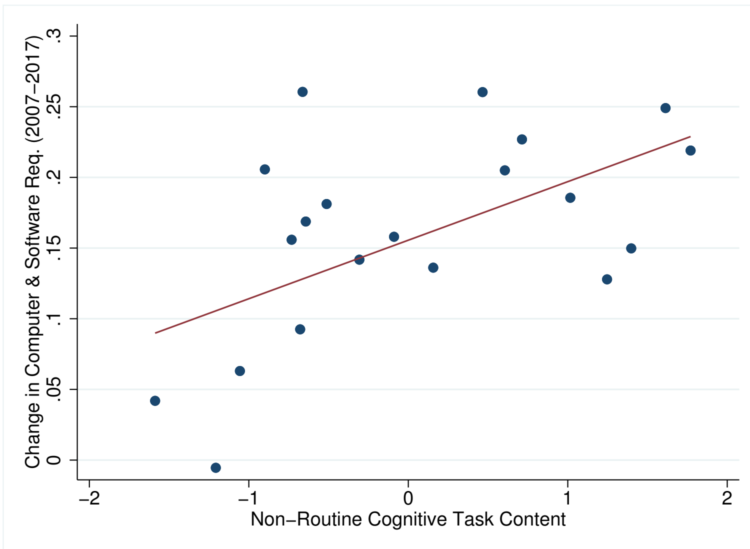
Figure A3 presents a series of binned scatter plots where on the x-axis we place occupations into ventiles based upon an occupation characteristic (e.g., share with a college degree, average age, etc.) and on the y-axis plot the average change in computer and software requirements within the ventile.[3] Occupations that have a larger share of college graduates (Panel (a)) as well

[3] Averages are employment weighted using 2007 employment as measured in the ACS. Additionally, the education, age, gender, and race composition of occupations is measured using the 2007 ACS.

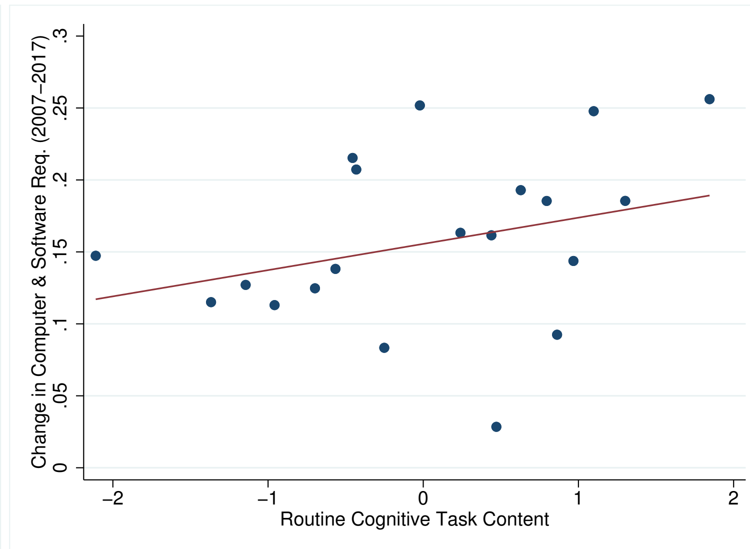
as occupations with workers of a higher average age (Panel (b)) experienced larger increases in computer and software requirements between 2007 and 2017. Panel (c) of Figure A3 shows that the gender composition of an occupation is not associated with changes in computer and software requirements. Finally, Panel (d) of Figure A3 shows that occupations which employ a larger share of white individuals have seen larger increases in computer and software requirements. Putting the results of Figures A2 and A3 together we see that occupations with larger increases in computer and software requirements tend to employ higher educated, older workers who perform jobs with a larger degree of cognitive tasks.

Figure A2: Changes in computer and software requirements by occupation characteristics

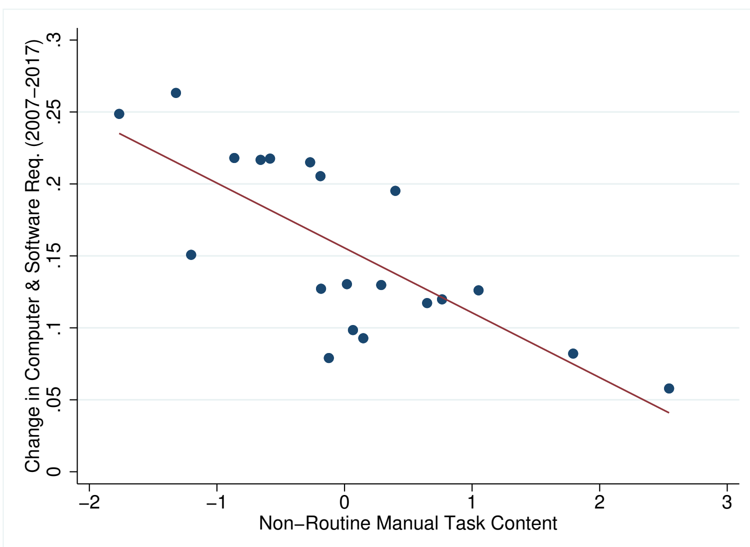
(a) Non-routine cognitive task content



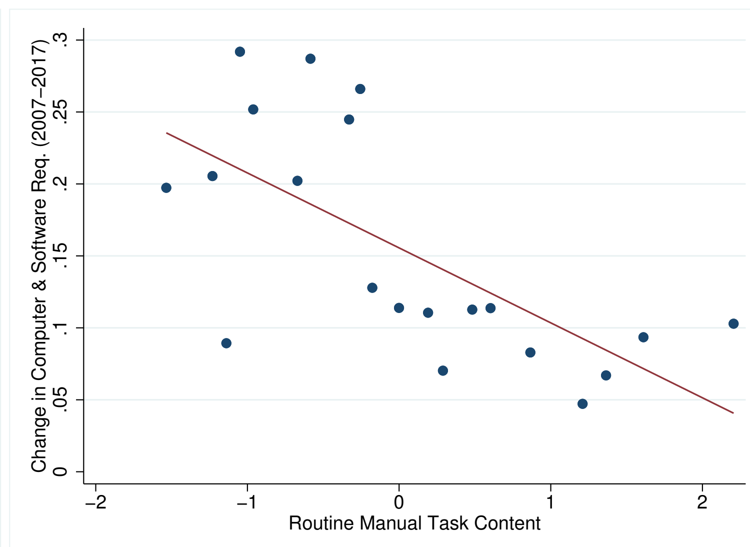
(b) Routine cognitive task content



(c) Non-routine manual task content

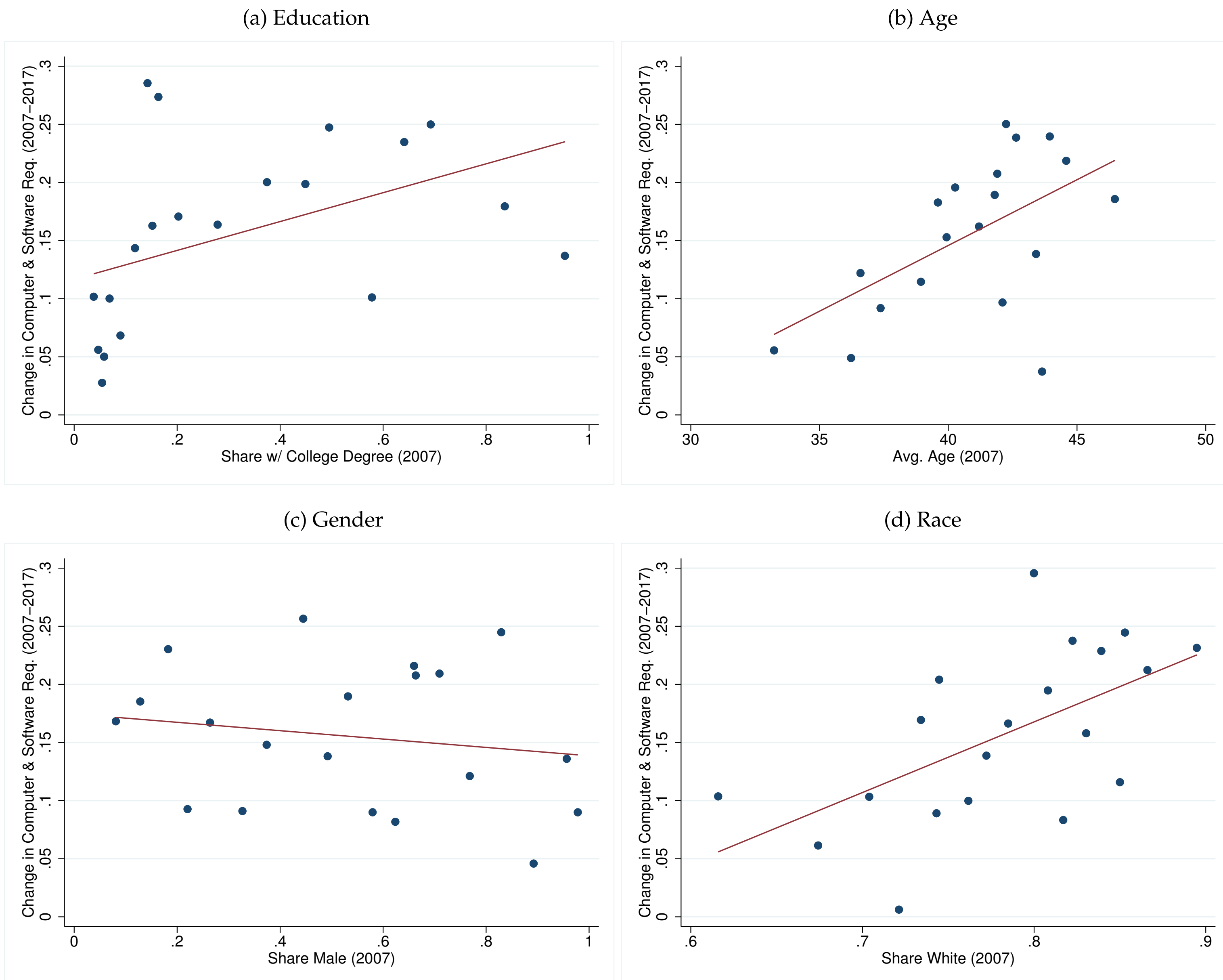


(d) Routine manual task content



Note: Figure presents binned scatter plots of characteristics on an occupation on the x-axis and the change in computer and software requirements between 2007 and 2017 as measured in the Burning Glass data on the y-axis. The task content measures are from Acemoglu and Autor (2011). All figures are employment weighted using 2007 occupation employment from the ACS.

Figure A3: Changes in computer and software requirements by occupation characteristics



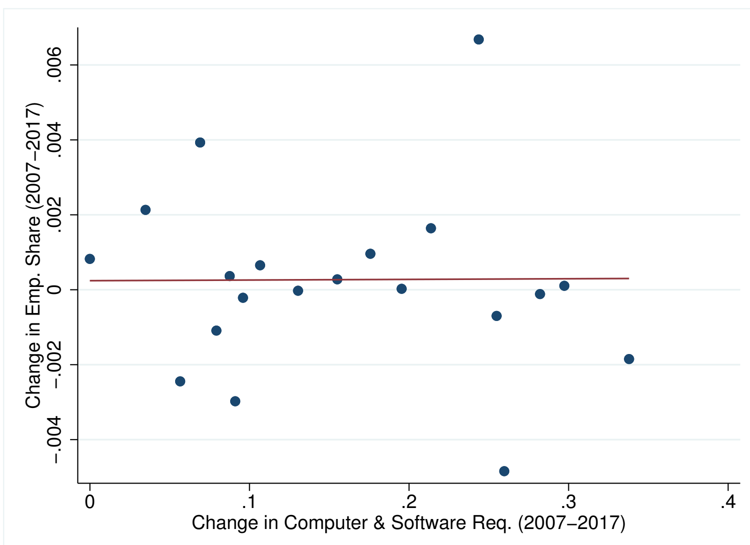
Note: Figure presents binned scatter plots of characteristics on an occupation on the x-axis and the change in computer and software requirements between 2007 and 2017 as measured in the Burning Glass data on the y-axis. Occupation characteristics are measured in the 2007 ACS.

B.3 Occupation trends by changes in computer and software req.

In this appendix, we examine changes in employment and wage structure between 2007 and 2017 by the degree of exposure to technological change as measured by changes in computer and software requirements. We measure employment shares and moments from the earnings distribution by occupation using data from the ACS.

We fist examine changes in employment share by exposure to technological change. Figure A4 presents a binned scatter plot of changes in computer and software requirements (x-axis) and changes in employment share (y-axis).[4] The figure shows that there is virtually no correlation between the degree of changes in computer and software requirements and changes in employment share. Thus, on average, occupations that are increasing their computer and software requirements are neither shrinking nor expanding.

Figure A4: Technological change and employment



Note: Figure presents binned scatter plots of the change in computer and software requirements between 2007 and 2017 as measured in the Burning Glass data on the x-axis, and change in employment share by occupation from the ACS on the y-axis. Figure is employment weighted using 2007 occupation employment from the ACS.

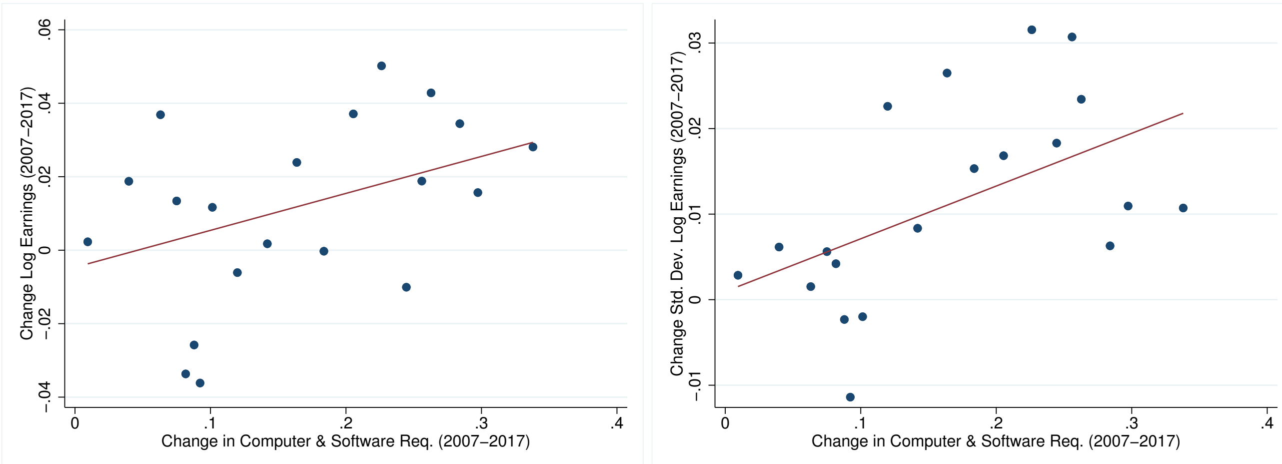
We next examine the implications of technological change for the evolution of earnings across and within occupations. To examine the evolution of earnings across and within occupations we use data on wage and salary income from the 2007 and 2017 American Community Survey (ACS). Using the ACS we measure the dispersion in earnings within an occupation using the standard deviation of log real earnings by occupation and year.[5] We additionally

[4] The figure is employment weighted using 2007 employment shares.

[5] For consistency with the sample in Section IV, we focus on workers between the ages of 25 and 65, with real

Figure A5: Technological change and earnings inequality

(a) Average earnings growth by occupation (b) Within occupation earnings dispersion



Notes: Panel (a) presents the log change in average real earnings in an occupation (y-axis) by exposure to technological change (x-axis). Panel (b) displays the change in the standard deviation of log earnings within an occupation (y-axis) by occupation exposure to technological change (x-axis). Exposure to technological change is measured by the change in the share of vacancies listing a computer or software requirement between 2007 and 2017 as measured in the Burning Glass database. Occupations are measured using four-digit SOC codes.

measure the average earnings by year and occupation to measure log earnings growth by occupation over this period. We then examine how the dispersion in earnings within an occupation and average earnings growth by occupation vary with the exposure of an occupation to technological change. Figure A5 presents the results.

Panel (a) of Figure A5 presents a binned scatter plot of exposure to technological change by occupation (x-axis) and the change in log average earnings by occupation between 2007 and 2017 (y-axis). The figure shows that occupations which have been more exposed to technological change have seen a larger increase in earnings over this time period (t-stat = 2.25). Panel (b) of Figure A5 presents a binned scatter plot of exposure to technological change by occupation (x-axis) and the change in the standard deviation of log earnings by occupation between 2007 and 2017 (y-axis). The figure shows that occupations which have been more exposed to technological change have seen a larger increase in the dispersion of earnings within an occupation (t-stat = 2.65). Hence, greater exposure to technological change increases within occupation earnings inequality.

annual earnings greater than 5,200. Earnings are made real using the CPI with 2012 as the base year. To minimize the impact of extreme values, we winsorize real earnings at the 1% level.

The results of this appendix showed that occupations which are more exposed to technological change are not experiencing a change in employment share. However, occupations more exposed to technological change are experiencing changes in wage structure with greater earnings growth and dispersion in earnings.

B.4 Geographic variation in technological change

In this appendix, we examine the degree of geographic variation in an occupations exposure to technological change. Let $z_{o,s,t}$ denote the share of vacancies in occupation o, state s, and year t that contain a computer or software related skill. Let $\Delta z_{o,s} = z_{o,s,2017} - z_{o,s,2007}$ denote the change in the share of vacancies in occupation o and state s that list a computer or software skill requirement between 2007 and 2017.

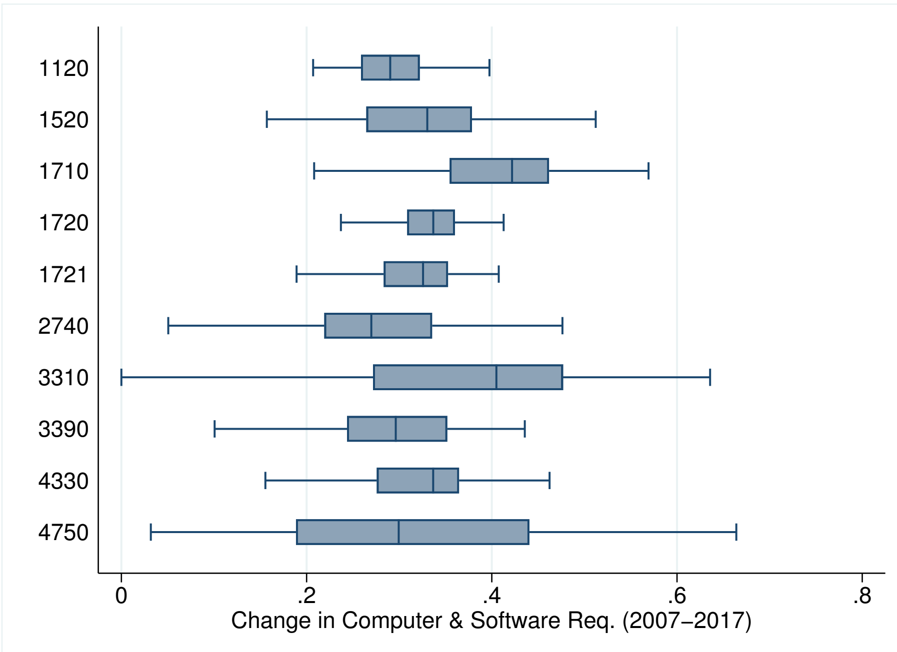
We find that there is substantial variation in the exposure of occupations to technological change across states. In Figure A6, we present a "box and whiskers" plot of the change in computer and software requirements across states for the 10 occupations with the largest increases in computer and software requirements nationally as presented in Table 1. In the figure the shaded region represents the range of observations within the 25th and 75th percentile for each occupation with the vertical line in the shaded region representing the median. The lines coming out of the shaded region cover the set of observations within 1.5X the interquartile range (P75-P25). The figure demonstrates there is a wide dispersion in changes in computer and software requirements among occupations with large increases nationally. For example, Architects (SOC-4=1710), which had the largest increases nationally, see an increase in computer and software requirements of less than 0.2 in some states, and over 0.50 in other states. As an even more extreme example among supervisors of protective service workers (SOC-4=3310), there is a state where there is no increase in computer and software requirements, while other states have an increase of over 0.60.

In Appendix C.11.2, we use the state-level of measures of exposure to technological change in our empirical analysis and show that we obtain very similar results.

B.5 Comparison to other measures of technological change

In this appendix, we compare our measure of technological change based upon changes in computer and software requirements over time from online vacancies to other measures of technological change. We first compare our estimate to changes in computer skills recorded in O*NET (Appendix B.5.1). We then compare our measure of technological change to the measure of skill change from Deming and Noray (2020) (Appendix B.5.2).

Figure A6: Geographic variation in technological change



Note: The figure shows a box and wisker plot of the change in computer and software requirements across states by four-digit SOC code. We present the box and wisker plot for the 10 occupations with the largest increases in computer and software requirements presented in Table 1. In the figure the shaded region represents the range of observations within the 25th and 75th percentile for each occupation with the vertical line in the shaded region representing the median. The lines coming out of the shaded region cover the set of observations within 1.5X the interquartile range (P75-P25).

B.5.1 Comparison to O*NET

In this section, we compare our measure of technological change based upon changes in computer and software requirements in the Burning Glass database to changes in computer requirements as recorded in O*NET. O*NET contains information on the skills and knowledge required in different occupations, where the information is obtained by surveying individuals currently working in the occupation as well as occupational experts. In this section, we use the O*NET measure of the level of knowledge needed in computers and electronics for a given occupation.[6] This variable records the level of skill needed for an occupation with a range from 1-7, with higher values denoting a greater value of skills required. O*NET provides information on occupations up to the 7-digit SOC code level.

The O*NET database is published each year, but in each publication approximately 100 6-digit (or 7-digit) occupations are updated. To measure how computer requirements have changed over time we compare the level of computer skills recorded in Version 23 of O*NET (published in August 2018, containing data from 2011 to 2018) to the level recorded in Version 5 of O*NET (published in April 2003, containing data from 2002 and 2003.).[7] We measure the change in the level of computer knowledge needed in an occupation across these two vintages of the O*NET database. To account for any differences in reporting standards across the two vintages of O*NET, we studentize each variable within each vintage of O*NET before taking the difference across vintages.[8]

The process for updating the data in O*NET is such that often 6-digit occupations (or 7-digit occupations, when available) under the same four-digit occupation code (e.g., 13-10XX.X) will be updated at different times.[9] To better facilitate comparisons of changes in computer requirements in the Burning Glass data and O*NET, in Figure A7 for the change in computer and software requirements from Burning Glass we measure the change in computer requirements between 2007 (the first year of Burning Glass data) and the year the 6-digit occupation was updated in O*NET.[10]

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[6] The variable we use is O*NET code 2.C.3.a.

[7] We use Version 23 of O*NET to include data that covers the end of our Burning Glass sample. We use Version 5 as our initial O*NET sample to allow for as many occupations to be updated as possible, and more than once if possible. Version 5 of O*NET was the first version of O*NET published following a transition in the method for which O*NET data are collected. See `https://www.onetcenter.org/db_transitional.html` for additional details on this transition. The results presented in this Section are robust to considering alternative pairs of O*NET data. The historical O*NET records are available from `https://www.onetcenter.org/db_releases.html` (last accessed on October 30, 2021).

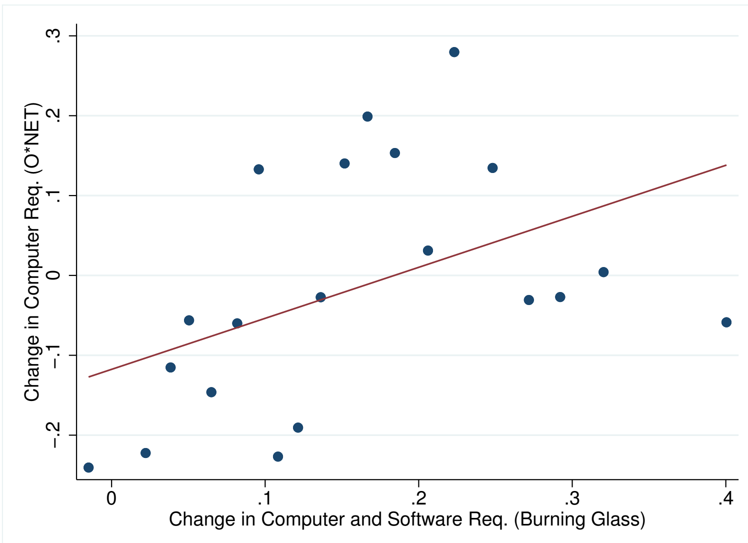
[8] In practice, studentizing the variables does not impact the results.

[9] For example, in Version 23 of O*NET the occupations which underlie the four-digit occupation 1310 have been updated between 2011 and 2017.

[10] In cases where the there is an underlying 7-digit occupation code, and the 7-digit occupations which underlie the 6-digit occupation code are updated in different years, we take the average year of updating. We find very

Figure A7 presents a binned scatter plot of changes in computer and software requirements as measured in the Burning Glass database (x-axis) and changes in computer requirements as measured in the O*NET database (y-axis). The figure shows that occupations which have seen a larger increase in the computer and software requirements as measured in the Burning Glass database have also seen a larger increase in the O*NET database (t-statistic = 2.42). Thus, changes in computer and software requirements in the Burning Glass database are predictive of changes in computer requirements in O*NET.

Figure A7: Changes in computer requirements from O*NET



*Note: The figure presents a binned scatter plot of changes in computer and software requirements as measured in the Burning Glass database (x-axis) and the change in computer requirements as measured in the O*NET database (y-axis).*

In Appendix C.7, we show that our empirical results linking greater exposure to technological change to larger earnings for displaced workers is robust to using changes in computer requirements from O*NET as our measure of technological change.

B.5.2 Comparison to Deming & Noray

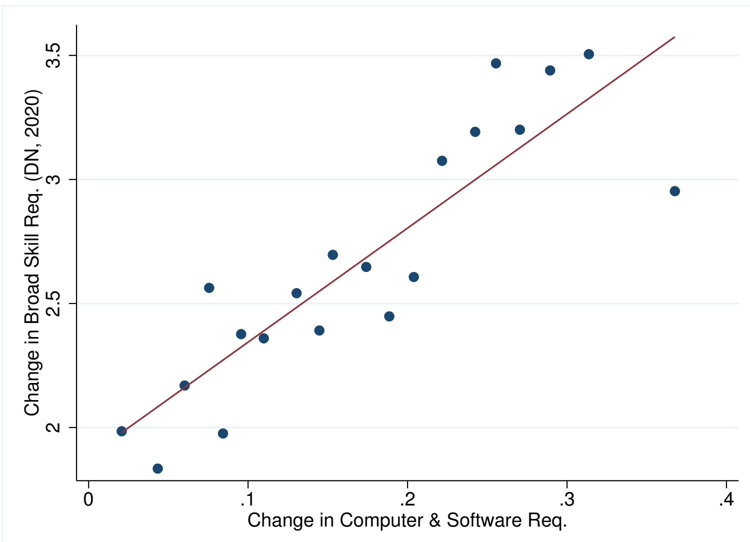
In this section, we compare our measure of technological change to the measure from Deming and Noray (2020), hereafter referred to as DN. DN create a measure of changes in skill requirements over time by occupation using the Burning Glass database. DN measure the share of vacancies listing S distinct skills in 2007 and 2019 by occupation. The authors then measure the

similar results if we use the minimum or maximum year of updating.

absolute value of the change in skill requirements across all S skills and take the sum across all S skills to create their measure of overall skill change for each occupation.

Our measure is based upon the same construct, namely to measure the share of vacancies listing a given set of skills in a year, and then measure that share over time. Our primary measure only considers one broad type of skill requirements, namely computer and software requirements. Conversely, DN consider a broader measure of skill changes, which encompasses computer and software requirements, as well as cognitive, social skills, etc. In Figure A8, we present a binned scatter plot of the change in computer and software requirements used in this paper (x-axis) and the change in broad skill requirements from Deming and Noray (2020) (y-axis) by four-digit SOC code. The figure shows that the two series are highly correlated with one another, with larger increases in computer and software requirements associated with greater overall skill change (t-statistics = 7.55).

Figure A8: Changes in skill requirements from Deming & Noray



Note: The figure presents a binned scatter plot of changes in computer and software requirements as measured in the Burning Glass database (x-axis) and the broad measure of changes in skill requirements from Deming and Noray (2020) (y-axis).

A benefit of the DN approach is that it creates a composite measure of skill changes in an occupation. A benefit of the approach we use is that it allows for estimating how changes in a given type of skill (e.g., computer & software, cognitive, and social) separately impact the outcomes of workers. For instance, in Table A4 we show that increases in social and manual skills are not associated with earnings changes around layoff, while change in computer and software requirements are associated with lower earnings following displacement.

C Additional results: outcomes of displaced workers

In this appendix, we present additional results relating the impact of technological change to the outcomes of displaced workers.

C.1 Heterogeneity

In this appendix, we examine if there is heterogeneity in the impact of exposure to technological change on the earnings losses of displaced workers. We first examine heterogeneity by age, education, and gender. Table A1 shows the results of estimating equation 1 where we split the sample by age, education, and gender. Column (2) of Table A1 shows the results of estimating equation 1 for workers who are between the ages of 25 and 44. The coefficient on the change in computer and software requirements is very similar to when we use the full sample of displaced workers (column (1) of Table A1). Column (3) Table A1 shows that we also obtain a virtually identical estimate of the impact of technological change on earnings changes around displacement when we limit the sample to workers between the ages of 45 and 65.

We next examine heterogeneity by education level and gender. In columns (4) and (5) of Table A1 we present results from estimating equation 1 for workers with 14 years of education or higher as well as workers with less than 14 years of education, respectively. The coefficient estimates on the change in computer and software requirements in each column is very similar to the coefficient from the full-sample estimate. Hence, there is minimial heterogeneity in the impact of exposure to technological change on earnings losses by education. In columns (6) and (7) of Table A1 we present results from estimating equation 1 for men and women, respectively. The coefficient estimates in columns (6) and (7) show the impact of exposure to technological change on earnings following displacement is very similar similar for both men and women. Thus, we also find that there is minimal heterogeneity in the impact of exposure to technological change by gender.

We next examine heterogeneity by an individuals prior earnings and the length of their unemployment spell. Using the ACS we measure median earnings by occupation and year, and classify each displaced worker by whether their earnings are above or below median real earnings in their pre-displacement occupation in the year of displacement. We then separately estimate equation 1 for individuals with pre-displacement earnings above (or below) median earnings in their pre-displacement occupation. Columns (2) and (3) of Table A2 presents the results. The negative and statistically significant coefficients in each column indicate that among both higher and lower earnings workers, we observe that exposure to technological change is associated with larger declines in earnings. The coefficient for individuals with below median prior earnings in their occupation is larger than for individuals with above median earnings, however the coefficients are not statistically different from one another (p-value = 0.288).

Finally, we examine the heterogeneity in the length of an individuals unemployment spell. In our sample, the median unemployment duration is 7 weeks and we split the estimation into individuals at or below the median as well as individuals above the median. Columns (4) and (5) of Table A2 presents the result of estimating equation 1 for individuals with an unemployment spell of 7 weeks or shorter and an unemployment spell longer than 7 weeks, respectively. The coefficient estimates on the change in computer requirements in columns (4) and (5) indicates that the impact of exposure to technological change on earnings following displacement is similar for both short and long unemployment durations. Further, the result that workers with short unemployment durations have lower earnings in response to technological change suggests that these workers were falling behind the technological frontier during their previous employment spell, and not only during the unemployment spell.

The results of this section show that the impact of exposure to technological change on earnings following job loss is similar across workers of different ages, education levels, and genders. Additionally, the result that exposure to technological change lowers earnings among individuals with short unemployment spells (7 weeks or less) suggest that these individuals are falling behind the technological frontier while in their prior job and not just during their unemployment spell. These results provide further support for Model Prediction 1 that greater exposure to technological change is associated with larger earnings losses following displacement. Further, the observation 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.

Table A1: Technological change and earnings losses after displacement by age, education, & gender

	Dependent variable: change in log earnings after displacement						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Chg. Computer Req.	-0.0345***	-0.0326**	-0.0345**	-0.0323**	-0.0322**	-0.0312**	-0.0342*
	(0.0122)	(0.0135)	(0.0141)	(0.0127)	(0.0160)	(0.0136)	(0.0174)
Observations	6,742	3,914	2,828	4,464	2,278	3,906	2,836
R-squared	0.234	0.218	0.244	0.240	0.230	0.186	0.308
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occ. Def.	SOC-4	SOC-4	SOC-4	SOC-4	SOC-4	SOC-4	SOC-4
	Full Sample	Age 25-44	Age 45-65	Edu >= 14 Yrs.	Edu < 14 Yrs.	Men	Women

Notes: The table shows regression results from the estimation of equation 1, where the dependent variable is the change in log earnings after displacement, for workers of different ages, education levels and genders. Earnings are measured in 2012 dollars. Controls include the change in ACS employment share between 2007 and 2017 and variables listed in the notes to Table 3. Clustered standard errors are in parentheses, where the clustering is performed at the occupation level. Occupations are classified using four-digit SOC codes. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Table A2: Technological change and earnings losses after displacement by prior earnings and unemployment duration

Dependent variable: change in log earnings after displacement

	(1)	(2)	(3)	(4)	(5)
Chg. Computer Req.	-0.0345***	-0.0598***	-0.0419**	-0.0349**	-0.0331**
	(0.0122)	(0.0149)	(0.0169)	(0.0142)	(0.0136)
Observations	6,742	3,300	3,442	3,428	3,314
R-squared	0.234	0.287	0.180	0.224	0.210
Controls	Yes	Yes	Yes	Yes	Yes
Occ. Def.	SOC-4	SOC-4	SOC-4	SOC-4	SOC-4
	Full Sample	Below Occ. Median	Above Occ. Median	Unemp. Dur. LTE 7 Wks.	Unemp. Dur. GT 7 Wks.

Notes: The table shows regression results from the estimation of equation 1, where the dependent variable is the change in log earnings after displacement, by workers prior earnings and unemployment duration. Earnings are measured in 2012 dollars. Controls include the change in ACS employment share between 2007 and 2017 and variables listed in the notes to Table 3. Clustered standard errors are in parentheses, where the clustering is performed at the occupation level. Occupations are classified using four-digit SOC codes. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

C.2 Changes in other skill requirements

In this appendix, we examine how changes in other skill requirements have an impact on the size of earnings losses after displacement.

We first examine a broad measure of changes in skill requirements from Deming and Noray (2020), hereafter referred to as DN. DN create a measure of changes in skill requirements over time by occupation using the Burning Glass database. DN measure the share of vacancies listing S distinct skills in 2007 and 2019 by occupation. The authors then measure the absolute value of the change in skill requirements across all S skills and take the sum across all S skills to create their measure of overall skill change for each occupation. This broad measure of changes in skill requirements includes changes in computer and software requirements, as well as changes in other types of skills such as cognitive and social skills. In Appendix B.5, we further compare the DN measure of skill changes with the baseline measure from this paper, based on changes in computer and software requirements, and find that the two measures are highly correlated.

We additionally examine the impact on earnings losses after displacement of changes in specific skill requirements. In particular, we measure changes in cognitive, social, and manual skill requirements using the skill requirements reported in the Burning Glass database.[11] We use a series of keywords for each skill type to identify if a vacancy lists a given type of skill. Table A3 presents the keywords that we use for each skill type.

Table A3: Keywords for identifying different skill types

Skill Type	Keywords
Cognitive	*Research, Analy, Decision, Solving, Math, Statistic, or Thinking*
Social	*Communication, Teamwork, Collaboration, Negotiation, or Presentation*
Manual	*Physical, or Lifting*

Notes: Table presents the keywords used to identify if a vacancy lists a given type of skill. The keywords for cognitive skills come from Hershbein and Kahn (2018). The keywords for social skills come from Deming and Kahn (2018).

Let $z^j_{o,t}$ denote the share of vacancies in occupation o listing skill $j \in \{broad, cognitive, manual, social\}$ in year t. Let $\Delta z^j_o = z^j_{o,2017} - z^j_{o,2007}$ denote the change in the share of vacancies listing skill j in occupation o between the years 2007 and 2017. In practice, we use the variable $\Delta\tilde{z}^j_o$ as our measure of the change in skill type j in occupation o, where to facilitate comparisons across different measures of skills, we normalize each measure of skill change (Δz^j_o) to be mean zero and have unit standard deviation. With the measure $\Delta\tilde{z}^j_o$, we measure the impact of the change in skill j on the outcome of workers displaced from occupation o by estimating

[11] Recent work by Deming (2017) has documented the rising importance of social skills in the labor market. Work by Deming and Kahn (2018) shows that social and cognitive skills are associated with higher wages.

$$\Delta ln(Earn_{i,o,t}) = \alpha + \beta^j \Delta \tilde{z}_o^j + \Gamma X_{i,t} + \epsilon_{i,o,t} \quad (1)$$

Table A4 presents the results of estimating equation 1. The first column of Table A4 presents the results from estimating equation 1 where the measure of skill change is our baseline measure of changes in computer and software requirements. As discussed above, workers who are displaced from occupations that are undergoing a greater increase in computer and software requirements experience larger earnings losses following displacement. Column (2) of Table A4 presents the results of estimating equation 1 where the measure of skill change is the *broad* measure from DN. The negative and statistically significant coefficient on changes in skill requirements in column (2) indicates that workers displaced from occupations with greater skill turnover experience larger earnings losses.

Table A4: Impact of changes in other skill requirements on outcomes of displaced workers

Dependent variable: change in log earnings after displacement

	(1)	(2)	(3)	(4)	(5)
Chg. Skill Req.	-0.0345***	-0.0490***	-0.0228*	0.0103	0.0124
	(0.0122)	(0.0133)	(0.0127)	(0.0111)	(0.00915)
Observations	6,742	6,742	6,742	6,742	6,742
R-squared	0.234	0.236	0.235	0.235	0.233
Controls	Yes	Yes	Yes	Yes	Yes
Occ. Def.	SOC-4	SOC-4	SOC-4	SOC-4	SOC-4
	Computer	Broad	Cognitive	Social	Manual

Notes: The table shows regression results from the estimation of equation 1. The broad measure of skill changes is from Deming and Noray (2020). Changes in cognitive, social, and manual skills are based on the keywords in Table A3. Each measure of skill change has been normalized to be mean zero and have unit standard deviation. Controls include the variables listed in the notes to Table 3 and the change in the 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. Occupations are classified using four-digit SOC codes. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

We next examine if changes in different types of skills (e.g., cognitive, social, etc.) have differential impacts on earnings after displacement. In column (3) of Table A4, we present the results of estimating equation 1 where the measure of skill change is the change in cognitive skill requirements. The coefficient on the change in cognitive skill requirements provides some evidence that increases in cognitive skill requirements are associated with lower earnings for displaced workers (p-value = 0.075). Column (4) presents results for changes in social skills. The coefficient is positive but not statistically significant, indicating that changes in social skill requirements are not associated with changes in earnings for displaced workers. Finally, in column (5), we find a similar result that changes in manual skills are not associated with changes in earnings for displaced workers.

The results of Table A4 show that we find a similar relationship between changes in broad skill requirements and earnings losses after displacement (column (2)) as we saw earlier for increases in computer and software requirements (column (1)). However, when we separately measure the impact of increases in different types of skill requirements over time (e.g., computer, cognitive, social, etc.), we see that these skills have differential impacts on the earnings path of displaced workers. We find that increases in computer and software requirements, and to some extent increases in cognitive skill requirements, are associated with larger earnings losses following displacement. Conversely, increases in social and manual skill requirements are not associated with lower earnings for displaced workers.

C.3 Additional results: occupation switching

In this appendix, we present additional results relating to occupation switching. We first show that workers more exposed to technological change are more likely to move to an occupation with lower computer and software requirements relative to their original occupation (C.3.1). We then show that workers more exposed to technological change are more likely to move to a lower-paying occupation (C.3.2).

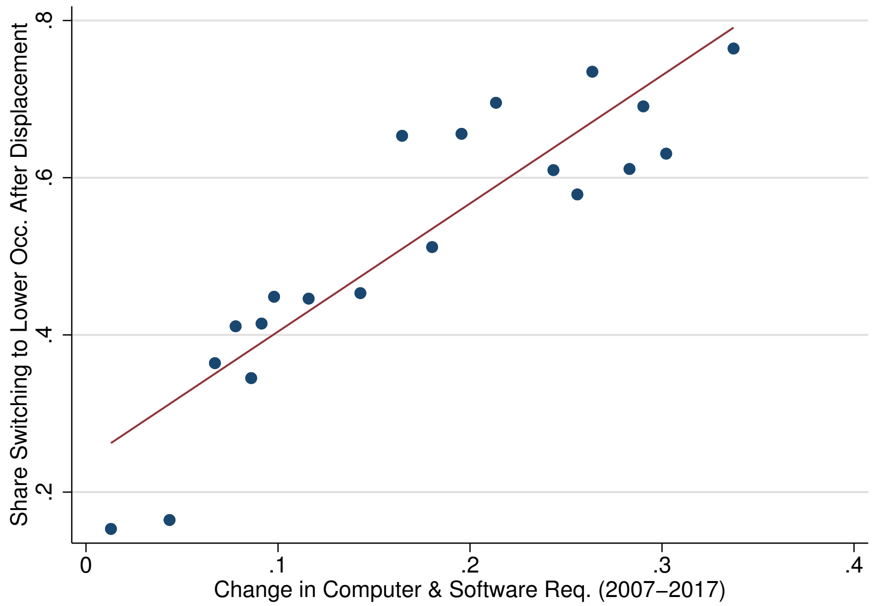
C.3.1 Moving to an occupation with lower computer and software req.

In this appendix, we examine which occupations individuals transition to after displacement. In particular, we examine if workers more exposed to technological change move to an occupation with a lower level of computer and software requirements relative to their original occupation. To the extent that workers transition, after displacement, to occupations with lower levels of computer and software requirements, this may indicate that these workers no longer have the skills to work in their original occupation.

Figure A9 presents a binned scatter plot of exposure to technological change (x-axis) and the probability of an occupation switcher moving an occupation with a lower level of computer and software requirements relative to their pre-displacement occupation (y-axis).[12] To identify instances of an individual moving to an occupation with a lower level of computer and software requirements relative to their original occupation, we compare the share of vacancies

[12] Note in the figure, we restrict the sample to individuals who have switched occupations following displacement.

Figure A9: Technological change and moving to an occupation with lower computer req.



Note: The figure shows the change in computer and software requirements between 2007 and 2017 by occupation as measured in the Burning Glass data (x-axis) and the share of workers moving to an occupation with a lower level of computer and software requirements after displacement relative to their original occupation (y-axis). The comparison on moving to an occupation with lower computer and software requirements is based upon 2007 values of computer and software requirements, and is among individuals who switched occupations after displacement. Occupations are classified using four-digit SOC codes.

listing a computer or software requirement in 2007 for the occupation from which an individual was displaced as well as the individual's current occupation. The figure shows that workers more exposed to technological change are more likely to transition to an occupation with lower computer and software requirements. For the most exposed workers, nearly 80% of occupation switches move to an occupation with a lower level of computer and software requirements. Conversely, among the least exposed workers only 30% transition to an occupation with lower computer and software requirements.

We next estimate equation 1 where the dependent variable is a dummy variable that is equal to 1 if an individual switches occupations after displacement and their new occupation has a lower level of computer and software requirements relative to their original occupation. Table A5 presents the results. Column (1) shows that individuals who are displaced from an occupation undergoing a greater increase in computer and software requirements have a higher probability of switching occupations and moving to an occupation with lower computer and software requirements. Column (2) and (3) show that this result is robust to controlling for changes in employment share in the occupation as well as an alternative classification of occupations. This result that workers more exposed to technological change are more likely to move to an occupation with lower computer and software requirements relative to their original occupation is suggestive that these workers no longer have the skills to work in their original occupation.

Table A5: Moving to an occupation with lower computer & software req.

Dependent variable: indicator for switching to occ. with lower computer req.

	(1)	(2)	(3)
Chg. Computer Req.	0.0661***	0.0665***	0.0429**
	(0.0236)	(0.0220)	(0.0216)
Chg. Emp. Share		-0.0258	0.00298
		(0.0167)	(0.0174)
Observations	4,310	4,310	4,494
R-squared	0.213	0.216	0.190
Controls	Yes	Yes	Yes
Occ. Def.	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 and moving to an occupation with lower computer and software requirements relative to an individual's original occupation. We estimate equation 1 among individuals who switched occupations after displacement. We classify moving to an occupation with lower computer and software requirements based upon the 2007 values of computer and software requirements. Controls 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. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

C.3.2 Moving to lower-paying occupation

In this appendix, we show that exposure to technological change increases the likelihood that workers transitions to a lower-paying occupation after displacement. Huckfeldt (2022) shows that earnings losses after displacement are concentrated among workers who transition to lower-paying occupations. These results suggest that these transitions to lower-paying occupations after displacement are in part due to within-occupation technological change.

We estimate equation 1 where the dependent variable is an indicator for switching to a lower-paying occupation after displacement. Table A6 presents the results. The positive and statistically significant coefficient on the change in computer requirements in column (1) indicates workers displaced from an occupation that is more exposed to technological change

Table A6: Technological change and moving to a lower-paying occupation

Dependent variable: indicator for switching to lower-paying occupation			
	(1)	(2)	(3)
Chg. Computer Req.	0.146***	0.148***	0.105***
	(0.0319)	(0.0313)	(0.0184)
Chg. Emp. Share		0.0203	0.0109
		(0.0253)	(0.0300)
Observations	6,742	6,742	6,742
R-squared	0.082	0.084	0.058
Controls	Yes	Yes	Yes
Occ. Def.	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 to a lower-paying occupation after displacement. We measure average earnings by occupation using the 2010 ACS. 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. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

are more likely to transition to a lower-paying occupation. In particular, in response to a one-standard deviation (SD) increase in computer and software requirements, a worker becomes 14.6 percentage points more likely to transition to a lower-paying occupation after displacement.[13] In column (2) we show that we obtain similar results when we control for the change in employment share in an individuals occupation. Additionally, the change in employment share in an individuals occupation does not increase the probability of moving to a lower-paying occupation in a statistically significant manner. Finally, in column (3) we show that we obtain similar results using the occupation classification from Autor and Dorn (2013).

C.4 Unemployment duration

In this appendix, we present results on the relationship between exposure to technological change and the duration of unemployment after displacement. We find workers more exposed to technological change *do not* have longer unemployment spells following displacement, and more broadly that exposure to technological change does not impact the length of an individual's unemployment spell.

For individuals in the DWS who regain employment after displacement the length of time until their first job is recorded. Using this measure of unemployment duration, we first examine

[13] In our sample, 33.6% of workers transition to a lower-paying occupation after displacement.

if workers displaced from occupations undergoing a greater degree of technological change have longer unemployment durations, which may lead to larger earnings losses.[14]

Table A7 presents the results of estimating equation 1 where the dependent variable is the length of an individual's unemployment spell after displacement. The coefficient on the change in computer requirements in column (1) of Table A7 indicates that changes in computer and software requirements do not affect the length of a displaced worker's unemployment spell after layoff (t-stat=0.19). In addition to not being statistically significant, the coefficient estimate in column (1) on the change in computer and software requirements is economically small. The coefficient estimate implies that an individual displaced at one-SD above the mean change in computer and software requirements has an unemployment spell that is approximately 0.21 weeks longer than an individual one-SD below the mean.

We next show that the result of workers more exposed to technological change not having longer unemployment spells is robust to additional controls and alternative classifications of occupations. In column (2) of Table A7 we control for changes in the employment share in an individuals pre-displacement occupation and find that greater exposure to computer and software requirements do not lengthen unemployment spells. Additionally, in column (3) we show that we obtain similar results using the occupation classification from Autor and Dorn (2013). In columns (1)-(3), we use the length of an individual's unemployment spell in weeks as the dependent variable. In columns (4)-(6), we use the log duration of an individual's unemployment spells to account for the skewness of the distribution of unemployment duration. The results presented in columns (4)-(6) also show that greater exposure to technological change does not increase the length of an individual's unemployment spell.[15]

C.4.1 Never regained employment

In the DWS individuals who have regained employment by the time of the survey are asked how long where they unemployed before starting their first job after displacement. In the section above, we only considered individuals who had regained employment when examining the relationship between exposure to new technology and the duration of unemployment after displacement. In this appendix, we expand our sample to include individuals who have

[14]The analysis performed in this section requires a worker to regain employment after displacement, which is consistent with our sample for measuring earnings losses. In Appendix C.4.1, we use the date of an individuals layoff and the survey date to infer the the length of unemployment spells for individuals who never regained employment after displacement. We find similar results when these individuals are included in the sample.

[15]Chetty (2008) censors the distribution of unemployment durations at 50 weeks to account for the skewness of unemployment durations. We find similar results using this approach.

Table A7: Technological change and unemployment duration

Dependent variable: length of unemployment spell after displacement						
	(1)	(2)	(3)	(4)	(5)	(6)
Chg. Computer Req.	0.104	0.0844	0.0860	0.0220	0.0220	0.0327
	(0.552)	(0.552)	(0.436)	(0.0313)	(0.0321)	(0.0287)
Chg. Emp. Share		-0.178	-0.0927		0.000655	0.0185
		(0.581)	(0.377)		(0.0341)	(0.0159)
Observations	6,742	6,742	6,742	6,742	6,742	6,742
R-squared	0.113	0.113	0.113	0.086	0.086	0.086
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Occ. Def.	SOC-4	SOC-4	AD	SOC-4	SOC-4	AD
Measure	Level	Level	Level	Log	Log	Log

Notes: The table shows regression results from the estimation of equation 1, where the dependent variable is the length of an individual's unemployment spell after displacement. In column (1)-(3) we measure the unemployment spell in weeks and in column (4)-(6) we take the log of unemployment duration. Controls include the age of the displaced worker, 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), (2), (4) and (5) classify occupations by four-digit SOC code, while columns (3) and (6) classifies occupations by Autor and Dorn (2013) occupation codes. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

never regained employment and examine the impact of technological change on the duration of unemployment. To incorporate individuals who have never regained employment after displacement, we use the date of an individual's layoff and the survey date to infer the duration of unemployment. Table A8 presents the results of estimating equation 1 where the dependent variable is the duration of unemployment, where the duration of individuals who have not regained employment is inferred. The coefficient on the change in computer requirements in column (1) indicates that being more exposed to technological change does not increase the length of an individual's unemployment spell. In columns (2) and (3) we show that this result is robust to controlling for changes in the employment share in an individual's occupation and using an alternative classification of occupations. In columns (4)-(6) of Table A8, we use the log of unemployment duration and find similar results. The results presented in Table A8 shows that the result that workers exposed to greater technological change do not have longer unemployment duration is not impacted by incorporating individuals who do not regain employment after displacement.

Table A8: Technological change and unemployment duration II

Dependent variable: length of unemployment spell after displacement

	(1)	(2)	(3)	(4)	(5)	(6)
Chg. Computer Req.	-0.837	-0.944	-0.547	-0.000379	-0.00402	0.0200
	(0.892)	(0.790)	(0.656)	(0.0360)	(0.0330)	(0.0282)
Chg. Emp. Share		-1.239*	-0.629		-0.0423	-0.0167
		(0.671)	(0.436)		(0.0327)	(0.0151)
Observations	10,519	10,519	10,519	10,519	10,519	10,519
R-squared	0.081	0.082	0.081	0.060	0.061	0.060
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Occ. Def.	SOC-4	SOC-4	AD	SOC-4	SOC-4	AD
Measure	Level	Level	Level	Log	Log	Log

Notes: The table shows regression results from the estimation of equation 1, where the dependent variable is the length of an individual's unemployment spell after displacement. For workers who do not regain employment after displacement, we infer the length of their unemployment spell using the time period since displacement. In column (1)-(3) we measure the unemployment spell in weeks and in column (4)-(6) we take the log of unemployment duration. Controls include the age of the displaced worker, 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, and an indicator for working full-time prior to displacement. Clustered standard errors are in parentheses, where the clustering is performed at the occupation level. Columns (1), (2), (4) and (5) classify occupations by four-digit SOC code, while columns (3) and (6) classifies occupations by Autor and Dorn (2013) occupation codes. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Finally, in section we examine how exposure to technological change impacts the probability of having an unemployment spell of a given duration. We perform this analysis for both individuals who regain employment after displacement and among all displaced workers. Table A9 presents the results of estimating equation 1 where the dependent variable is an indicator variable for having an unemployment spell of a given length (e.g., 3 months). In column (1) of Table A9 we examine how exposure to technological change impacts the probability of having an unemployment duration of 3 months. The coefficient on the change in computer requirements is not statistically significant indicating that workers more exposed to technological change are not more likely to have an unemployment spell that lasts at least 3 months (t-stat = 0.50). Columns (2)-(4) show that we find similar results for unemployment spells of 6, 9, and 12 months respectively. These results are among individuals who regain employment following displacement. In columns (5)-(8), we expand the sample to incorporate all displaced workers regardless of whether or not the individual regained employed following displacement. Among individuals who did not regain employment after displacement, we infer the length of their unemployment spell based upon their year of layoff and the time of the survey. Among this larger sample, we find similar results that greater exposure to technological change does not impact the probability of having an unemployment spell of a given length.

Table A9: Technological change and alternative unemp. duration lengths

Dependent variable: indicator for unemployment duration of a given length

	Employed Sample				Population Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Chg. Computer Req.	0.00578	-0.000759	-0.00370	-0.00342	0.00223	-0.00349	-0.00700	-0.00636
	(0.0117)	(0.0102)	(0.00836)	(0.00735)	(0.0106)	(0.0107)	(0.0101)	(0.00969)
Observations	6,742	6,742	6,742	6,742	10,519	10,519	10,519	10,519
R-squared	0.067	0.075	0.081	0.079	0.057	0.066	0.076	0.079
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occ. Def.	SOC-4	SOC-4	SOC-4	SOC-4	SOC-4	SOC-4	SOC-4	SOC-4
Unemp. Duration	3 Mo.	6 Mo.	9 Mo.	12 Mo.	3 Mo.	6 Mo.	9 Mo.	12 Mo.

Notes: The table shows regression results from the estimation of equation 1 where the dependent variable is an indicator for having an unemployment duration of a given duration. For columns (1)-(4) controls include the variables listed in the notes to Table A7. For columns (5)-(8) controls include the variables listed in the notes to Table A8. Clustered standard errors are in parentheses, where the clustering is performed at the occupation level. Employed sample refers to displaced workers who have regained employed after displacement. The population sample refers all displaced workers regardless of whether or not they regained employment after displacement. Occupations are classified using four-digit SOC codes. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

C.5 Additional details: Technological change & displacement probability

In this appendix, we present additional details about the sample we use to examine how exposure to technological change impacts the probability of displacement. We additionally provide graphical evidence for the lack of a relationship between exposure to technological change and the probability of displacement.

Sample construction. The DWS draws its sample by asking if an individual has been displaced within the past three years. The DWS defines an individual as being displaced if they lost their job for one of three reasons: (1) their company or plant shutting down, (2) their shift or position being eliminated, or (3) having insufficient work. From an individual's yes/no answer to this question, we can examine the likelihood that an individual with a given set of characteristics (e.g. age, education, occupation, etc.) is at risk of being displaced. For individuals who report that they experienced a displacement, we classify their occupation as the occupation prior to displacement. For individuals who do not report being displaced we classify their occupation as their current occupation.[16] To be consistent with our baseline sample in Section IV we restrict the sample to individuals between the ages of 25 and 65.

Graphical evidence. In this section, we provide graphical evidence on how the likelihood of becoming displaced varies with the rate of technological change in an occupation. In Figure A10 we present a binned scatter plot of the probability of being displaced (y-axis) by the rate of technological change in an individual's occupation between 2007 and 2017 (x-axis). This figure can be interpreted as the likelihood of being displaced by the rate of technological change in an individual's occupation. The red line in the figure shows that there is a relatively flat profile.[17] Hence, the probability that an individual is displaced does not vary by their exposure to technological change.

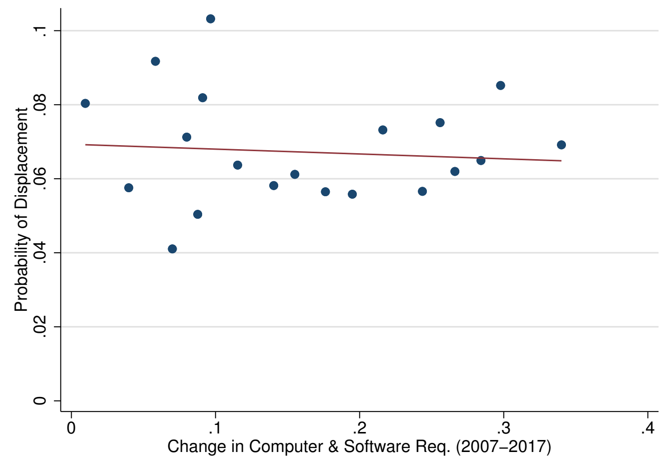
C.6 Additional details and results: CPS outgoing rotation groups

In this appendix, we present additional details about the CPS outgoing rotation group sample (CPS-ORG) as well as additional results from using this sample.

[16] Current occupation is recorded as part of the basic CPS questions.

[17] As we show in Section IV.E, the slope of the trend line is not statistically different from zero with a t-statistic of -0.39. Additionally, note that the binned scatter plot is weighted using the DWS supplement weights. Since these regressions include both displaced and non-displaced workers, the regressions are effectively weighted using the employment share across occupations in the DWS survey months.

Figure A10: Probability of displacement and technological change



Note: The figure shows a binned scatter plot of the probability of displacement (y-axis) by the change in computer and software requirements in an individuals occupation between 2007 and 2017. Occupations are classified using four-digit SOC codes.

Sample construction. In the CPS survey, individuals are included in the survey for four consecutive months (months 1-4 of the survey), not surveyed for 8 months (months 5-12 of the survey), and then surveyed for an additional 4 consecutive months (months 13-16 of the survey). In the final month of each 4-month wave (months 4 and 16 of the survey) individuals are asked about their earnings and hours worked. These final months of each 4-month wave are referred to as the "outgoing rotation groups," (ORG). For individuals in the CPS-ORG, we observe their employment status as well as occupation and earnings for individuals who are employed at the time of the survey. This structure allows us to examine how individuals transition across occupations and how their earnings evolve over a 12 month period. We use this sample as it gives us a consistent sample to jointly consider the evolution of occupation and earnings dynamics in response to exposure to technological change.[18]

Additional results: occupation switching Using the CPS-ORG sample, we examine the impact of exposure to technological change on the likelihood of switching occupations. The simple

[18]To align with our baseline sample in Section IV, we include individuals between the age of 25 and 65 in the analysis. We additionally require that the individual have real weekly earnings greater than \$100 (in 2012 dollars) in both CPS-ORG observations. We additionally remove individuals whose earnings are top-coded or allocated. Finally, to focus the analysis on workers who are employed in both periods (and limit the role of extensive margin changes) we restrict the sample to workers whose change in log earnings is between -0.50 & 0.50 log points. This restrictions decreases the sample by approximately 10% and the results shown are robust to alternative specifications.

model of technological change presented in Section I introduced occupation switching as a key contributor to the evolution of earnings in response to technological change. In particular, the theory predicted that workers in occupations more exposed to technological change would be more likely to switch occupations. Recall that in Section IV.D, we showed that displaced workers more exposed to technological change were more likely to switch occupation following displacement. In this section, we find similar results among a broader sample of workers.

The first column of Table A10 presents the results of estimating equation 1 where the dependent variable is an indicator for switching occupations. The positive and statistically significant coefficient in the first column of Table A10 indicates that workers employed in an occupation more exposed to technological change are more likely to switch occupations. In particular, comparing a worker one-SD above the mean change in computer and software requirements to one-SD below, the worker one-SD above the average is over 14 percentage points more likely to switch occupations.[19] In columns (2) and (3) of Table A10, we show that these results are robust to controlling for the change in employment share in an occupation (column (2)) and using the occupation classification from Autor and Dorn (2013) (column (3)). These result highlights that the phenomenon of exposure to technological change increasing the probability of occupation switching applies more broadly to workers and not only to displaced workers.

Table A10: Technological change and occupation switching in CPS-ORG

Dependent variable: indicator for switching occupations

	(1)	(2)	(3)
Chg. Computer Req.	0.0710***	0.0689***	0.0512***
	(0.0218)	(0.0204)	(0.0167)
Chg. Emp. Share		-0.0172	-0.0122
		(0.0163)	(0.0128)
Observations	254,332	254,332	254,332
R-squared	0.032	0.034	0.024
Controls	Yes	Yes	Yes
Occ. Def.	SOC-4	SOC-4	AD

Notes: The table shows regression results from the estimation of equation 1 using data from the CPS-ORG. Controls include year fixed effects, gender fixed effects, as well as controls for age, years of completed education, initial level of computer requirements in 2007, and the change in employment share between 2007 and 2017 in the ACS for the individuals initial occupation. Clustered standard errors are in parentheses, where the clustering is performed at the occupation level. Columns (1)-(2) classify occupations by four-digit SOC code, while column (3) classifies occupations by Autor and Dorn (2013) occupation codes. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

[19] In the CPS-ORG, 36.4% of individuals switch occupations across the 12-month period.

C.7 Measuring technological change in O*NET

In this appendix, we examine the robustness of our empirical results to using the measure of changes in computer requirements from O*NET. See Appendix B.5.1 for details on the O*NET survey. To facilitate comparison to our baseline results, in this appendix we measure the change in computer requirements as reported in O*NET by four-digit SOC across Version 23 of O*NET (published in August 2018, and containing data from 2011 to 2018) and Version 5 of O*NET (published in April 2003, which contains data from 2002 and 2003).[20]

Let $\Delta Comp_{i,o,t}^{ONET}$ denote the change in the level of computer knowledge required in occupation o between the two vintages of O*NET data for an individual i displaced from that occupation, who is in the DWS in year t. We normalize the change in computer knowledge from O*NET to be mean zero and have unit standard deviation. Let $X_{i,t}$ denote a series of control variables that include the change in the employment share of the occupation between 2007 and 2017 in the ACS, age of the displaced worker, the log duration of their unemployment spell after layoff, tenure prior to layoff, years of educational attainment, a series of dummy variables for the DWS 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 DWS survey as well as the year the occupation was updated in O*NET, as well as the share of reports in O*NET conducted by an occupational expert for that occupation. The specification we use is of the form:

$$Y_{i,o,t} = \alpha + \beta \Delta Comp_{i,o,t}^{ONET} + \Gamma X_{i,o,t} + \epsilon_{i,o,t} \tag{2}$$

Table A11 contains the results of estimating equation 2. Column (1) of Table A11 shows the results of estimating equation 2 where the dependent variable is the change in log earnings after displacement. The negative and statistically significant coefficient indicates that workers displaced from occupations undergoing a larger increase in computer requirements, as measured in O*NET, experience a larger decline in earnings following displacement. In particular, comparing a worker displaced at one-SD above the mean change in O*NET compared to a worker one-SD below the mean, the worker displaced one-SD above the mean has a decline in earnings that is over 4.6 percentage points larger. Hence, we find similar results using changes in computer requirements in O*NET as we do using changes in computer and software requirements from the Burning Glass database.

[20] Computer requirements are recorded in O*NET as O*NET code 2.C.3.a. Note that our results are robust to considering alternative versions of the O*NET database.

Table A11: Measuring technological change using O*NET

	(1) Chg. Log Real Earnings	(2) Switch Occ. (d)	(3) Unemp. Dur	(4) Emp. (d)
Chg. CPU Req. O*NET	-0.0234**	0.0510***	-0.293	0.00778
	(0.00984)	(0.0174)	(0.369)	(0.00499)
Observations	6,742	6,742	6,742	10,519
R-squared	0.234	0.032	0.113	0.136
Controls	Yes	Yes	Yes	Yes
Occ. Def	SOC-4	SOC-4	SOC-4	SOC-4
Sample	Emp. Sample	Emp. Sample	Emp. Sample	Pop. Sample

*Notes: This table shows regression results from the estimation of equation 2. Clustered standard errors are in parentheses, where the clustering is performed at the occupation level. The symbol (d) indicates a dummy variable. Earnings are measured as the difference in log real earnings, where earnings are measured in 2012 dollars. Controls include the change in the employment share of the occupation between 2007 and 2017 in the ACS, age of the displaced worker, the log duration of their unemployment spell after layoff, tenure prior to layoff, years of educational attainment, a series of dummy variables for the DWS 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 DWS survey as well as the year the occupation was updated in O*NET, as well as the share of reports in O*NET conducted by an occupational expert for that occupation. Note in columns (3) and (4) we do not use unemployment duration as a control and additionally in column (4) we do not use the indicator for full-time after displacement as a control. Occupation switching is defined using four-digit SOC codes. The employed sample (columns (1)-(3)) refers to individuals in the DWS who are employed both prior to and after displacement, while the population sample (column (4)) is all individuals who are employed prior to displacement.* ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

We next examine the mechanism through which changes in computer requirements impact earnings following displacement using the O*NET data. In column (2) of Table A11 we present the results of estimating equation 2 where the dependent variable is an indicator variable for whether or not a worker switched occupations following displacement. The positive and statistically significant coefficient on the change in computer requirements indicates that workers displaced from occupations undergoing a greater increase in computer requirements, as measured in O*NET, are more likely to switch occupations following displacement. The coefficient estimate implies that a worker displaced at one-SD above the mean change in computer requirements in O*NET is over 10 percentage points more likely to switch occupations than a worker one-SD below the mean.

We next examine how changes in computer requirements in O*NET impact the length of an individual's unemployment spell following displacement. In column (3) of Table A11 we present the results of estimating equation 2 where the dependent variable is an individuals unemployment duration following displacement. The coefficient on the change in computer requirements, as measured in O*NET, indicates that changes in computer requirements are not associated with longer/shorter unemployment spells following displacement. Finally, in column (4) we examine the propensity to be employed following displacement by changes in computer requirements as measured in O*NET. The coefficient on changes in computer requirements shows that changes in computer requirements in O*NET are not associated with changes in the probability of being employed following displacement.

This results of this appendix show that our results are robust to an alternative measure of technological change using data from O*NET. In particular, we find that workers displaced from occupations undergoing a larger increase in computer requirements, as measured in O*NET, experience a larger decline in earnings. Additionally, similar to our results using the Burning Glass database, we find evidence that the mechanism works through occupation switching and not having a longer unemployment duration.

C.8 Alternative timing

One potential concern with the results presented in Section IV is that the measure of technological change is over the entire time period (2007-2017), while the change in earnings is measured around the individual's displacement event. In this appendix, we consider an alternative timing assumption for the measure of technological change for each worker. In particular, we exploit the information from the Displaced Worker Supplement on the year that an individual was hired from the job in which they were displaced as well as the information on the year in which they were displaced. From these dates we can construct a measure of the amount of technological change which occurred in an individual's occupation during their employment spell.[21] Using this measure of technological change, we re-perform our empirical analysis of the impact of technological change on the outcomes of displaced workers. Table A12 presents the results using this measure of technological change with alternative timing. The results in Table A12 show that our results are robust to this alternative timing assumption. In particular, workers more exposed to technological change, during their pre-displacement employment match, experience: (1) larger earnings losses following displacement, (2) are more likely to switch occupations, but (3) *do not* have longer unemployment spells and (4) are *equally* likely to be employed after displacement.

[21] For jobs that began prior to 2007, we use the level of computer and software requirements in 2007 as the level of computer and software requirements at the time of the hire. For the years 2008 and 2009, when the Burning Glass data is not available, we linearly interpolate the level of computer and software requirements in an occupation using the 2007 and 2010 levels of computer and software requirements. We additionally normalize our measure of the change in computer and software skills during an individuals employment spell to be mean zero and have unit standard deviation.

Table A12: Impact of technological change on displacement outcomes: alternative timing

	(1) Chg. Log Real Earnings	(2) Switch Occ. (d)	(3) Unemp. Dur	(4) Emp. (d)
Chg. Computer Req.	-0.0294***	0.0355**	-0.229	-0.00105
	(0.00880)	(0.0160)	(0.338)	(0.00678)
Observations	6,742	6,742	6,742	10,519
R-squared	0.234	0.026	0.114	0.135
Controls	Yes	Yes	Yes	Yes
Occ. Def.	SOC-4	SOC-4	SOC-4	SOC-4

Notes: The table shows regression results from the estimation of equation 1. Earnings are measured in 2012 dollars. The change in computer and software requirements is measured between the year an individual was displaced and the year they were hired using the Burning Glass data, and is normalized to be mean zero and have unit standard deviation. Controls include the change in ACS employment share between 2007 and 2017 and variables listed in the notes to Table 3. Note in columns (3) and (4) we do not use unemployment duration as a control and additionally in column (4) we do not use the indicator for full-time employment after displacement as a control. Occupation switching is defined using four-digit SOC codes. The employed sample (columns (1)-(3)) refers to individuals in the DWS who are employed both prior to and after displacement, while the population sample (column (4)) is all individuals who are employed prior to displacement. Clustered standard errors are in parentheses, where the clustering is performed at the occupation level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

C.9 Technological change in an earlier time period (1982-2000)

In this appendix, we consider an earlier time period to examine the impact of technological change on the outcomes of displaced workers. We use data on skill requirements from newspaper vacancy postings collected by Atalay et al. (2020) to measure technological change between 1982 and 2000 at the occupation level.[22] Using the 1984-2000 waves of the DWS, we examine how technological change impacts the size of earnings losses after displacement as well as the probability of being displaced. We find results consistent with our baseline estimates, that technological change does not impact the probability of being displaced, but workers displaced from occupations undergoing a greater degree of technological change experience a larger decline in earnings after job loss.

[22] We thank the authors for generously making their data available online. The data and programs are available at: https://occupationdata.github.io/.

Data overview

In this subsection, we discuss the data we use to consider the impact of technological change on the outcomes of displaced workers from 1982 to 2000.

Atalay et al. (2020) collect the text from job vacancies advertised in the *New York Times*, *Wall Street Journal*, and *Boston Globe* from 1940 through 2000. From the raw text they identify the skills listed in each vacancy posting as well as the occupation for the vacancy. Atalay et al. (2020) create and report many measures of the task content included in the newspaper vacancies. We use their measure of computer and software requirements, which counts per 1000 words of text, the number of words that contain the keywords: "computer," "software," or "spreadsheets." To measure technological change at the occupation level, we measure the change in the share of words which list a computer or software skill between 1982 and 2000 by occupation. For ease of interpretation, we normalize the change in the share of words listing a computer or software skill to be mean zero and have unit standard deviation. Given the longer and earlier time period for this analysis, we use the time-consistent occupation classification from Autor and Dorn (2013).

The data on displaced workers comes from the Displaced Workers Supplement (DWS) to the CPS. We use the 1984-2000 waves of the DWS, which identify workers who were displaced between 1982 and 2000. To restrict our sample to workers who lose their job due to reasons that are exogenous to their characteristics, we focus on workers who are displaced, and list the reason of their displacement as being either (1) their company or plant shutting down, (2) their shift or position being eliminated, or (3) having insufficient work.[23] To make the sample consistent with the sample in our baseline analysis, we additionally remove individuals who report that they expect to be recalled to their prior job and individuals who were displaced more than three years from the time of the survey. To examine the impact of technological change on earnings following displacement in the 1982-2000 time period, we create 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. To align with our baseline sample in Section IV we additionally require that individuals have non top-coded earnings both prior to displacement and after displacement. This results in a sample of 14,010 individuals. Table A13 provides summary statistics on the displaced workers from the 1982-2000 time period.

Using this sample of displaced workers and the measure computer and software requirements from Atalay et al. (2020), we estimate the impact of technological change on the outcomes

[23] This restriction removes individuals who are displaced due to a seasonal job ending, their self-operated business failing, or listing "other" as the reason for there displacement. These restrictions also align with the types of displacements considered in our baseline sample.

Table A13: Summary statistics: 1982-2000 DWS

	(1) Displaced Workers	(2) Non-Displaced Workers
Chg. Computer Req.	0.028	0.023
Weekly Real Earnings (Displaced Job)	$835.09	-
Weekly Real Earnings (Current Job)	$746.46	$836.47
Years Since Displacement	1.94	-
Switch Occ. (d)	0.65	-
Age	38.36	40.20
Years of Education	13.45	13.61
Observations	14,010	82,516

Notes: See Section C.9 for sample selection criteria. For the non-displaced sample these variables are based on the worker's current occupation. Weekly earnings are measured in 2012 dollars. The symbol (d) denotes a dummy variable.

displaced workers for the years 1982 to 2000.

Earnings after displacement. We first examine how technological change impacts the outcomes of displaced workers in the 1982-2000 time period. Table A14 presents the results of estimating equation 1 where the dependent variable is the change in log earnings after displacement for workers displaced between 1982 and 2000. The negative and statistically significant coefficient on the change in computer and software requirements indicates that workers more exposed to technological change experienced a larger decline in earnings. In column (2) of Table A14 we control for the change in employment share between 1980 and 2000 and find that the coefficient on changes in computer and software requirements is largely unchanged.[24] Finally in column (3) of Table A14 we restrict the sample to workers who are employed full-time prior to displacement and after displacement. Among this sample we find a similar relationship between exposure to technological change and larger earnings losses following displacement. This result among full-time workers suggests that the declines in earnings are due to declines in wages rather than hours. The results of this appendix show that exposure to technological change has decreased earnings after displacement in earlier time period and not only over the past decade.

Probability of displacement. We next examine how technological change impacts the probability of being displaced for the 1982-2000 time period. Table A15 presents the results of esti-

[24] We measure the change in employment share by occupation between 1980 and 2000 using the 5% national samples provided by IPUMS-ACS.

Table A14: Impact of technological change on outcomes of displaced workers: 1982-2000

Dependent variable: change in log earnings after displacement			
	(1)	(2)	(3)
Chg. Computer Req. (1982-2000)	-0.0134**	-0.0123**	-0.0136***
	(0.00532)	(0.00533)	(0.00515)
Chg. Emp. Share (1980-2000)		0.00814	0.00143
		(0.00848)	(0.00718)
Observations	14,010	14,010	10,463
R-squared	0.172	0.172	0.040
Controls	Yes	Yes	Yes
Occ. Def.	AD	AD	AD
Sample	Full Sample	Full Sample	Full Time Only

Notes: This table shows regression results from the estimation of equation 1 where the dependent variable is the change in log earnings after displacement. The change in computer and software requirements is measured between 1982 and 2000 using the data from Atalay et al. (2020), and the change in employment share is measured between 1980 and 2000 using the 5% national samples from IPUMS-ACS. The change in computer requirements and employment share are both normalized to be mean zero and unit standard deviation. Clustered standard errors are in parentheses, where the clustering is performed at the occupation level. Controls include the age of the displaced worker, tenure prior to layoff, years of educational attainment, and level of computer requirements in 1982 as well as a series of dummy variables for 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. Earnings are measured as the difference in log real earnings, where earnings are measured in 2012 dollars. Occupations are classified using Autor and Dorn (2013) occupation codes. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

mating equation 1 where the dependent variable is an indicator for being a displaced worker. Column (1) of Table A15 shows that workers more exposed to technological change between 1982 and 2000 were not more likely to be displaced. In columns (2)-(4) of Table A15 we show that this result is robust to a series of additional controls for the change in employment in an individual's occupation (column (2)), year fixed effects (column (3)) as well as a series of demographic controls (column (4)).

C.10 Impact of technological change on employment and labor force exit

In this appendix, we examine if exposure to technological change impacts the probability of being employed as well as exiting the labor market after displacement.

To examine employment and labor force exit after displacement, in this appendix we use a sample of all individuals between the ages of 25 and 65 who were identified as displaced in the

Table A15: Probability of displacement and technological change: 1982-2000

Dependent variable: indicator for displaced worker

	(1)	(2)	(3)	(4)
Chg. Computer Req. (1982-2000)	0.00394	0.00370	0.00373	0.00382
	(0.00357)	(0.00352)	(0.00351)	(0.00340)
Chg. Emp. Share (1980-2000)		-0.00230	-0.00232	-0.00194
		(0.00294)	(0.00290)	(0.00218)
Observations	443,843	443,843	443,843	443,843
R-squared	0.000	0.000	0.002	0.005
Year FE	No	No	Yes	Yes
Controls	No	No	No	Yes
Occ. Def.	AD	AD	AD	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. The change in computer and software requirements is measured between 1982 and 2000 using the data from Atalay et al. (2020), and the change in employment share is measured between 1980 and 2000 using the 5% national samples from IPUMS-ACS. The change in computer requirements and employment share are both normalized to be mean zero and unit standard deviation. Controls include age, the level of computer requirements in 1982 in the worker's occupation, years of educational attainment, and a dummy variable for gender. Clustered standard errors are in parentheses, where the clustering is performed at the occupation level. Occupations are classified using Autor and Dorn (2013) occupation codes. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

DWS with non top-coded earnings prior to displacement.[25] This results in a sample of 10,519 individuals.

To examine how exposure to technological change impacts the probability of regaining employment or exiting the labor force, we estimate equation 1 where the dependent variable is an indicator for being employed or out of the labor force at the time of the DWS survey. Table A16 presents the results of estimation equation 1 where the dependent variable is an indicator for being employed at the time of the DWS survey. The coefficient on the change in computer requirements in column (1) is positive, but statistically insignificant indicating that exposure to technological change does not impact the probability of being employed after displacement. In column (2), we include the change in employment share in an individual's occupation and find a similar result. Finally, in column (3) we use the Autor and Dorn (2013) occupation classification and find that exposure to technological change does not impact the probability of being employed after displacement.

Table A17 presents the results of estimation equation 1 where the dependent variable is an

[25]We impose the non-top coded earnings condition to maintain consistency with our employed sample. We additionally require that an individual have weekly real earnings greater than \$100 (in 2012 dollars) prior to displacement. Our results are robust to this minimum earnings threshold.

indicator for not being in the labor force at the time of the DWS survey. The coefficient on the change in computer requirements in column (1) is negative, but statistically insignificant indicating that exposure to technological change does not impact the probability of exiting the labor force. In columns (2) and (3) of Table A17 we find similar results controlling for the change in employment share in an individual's occupation as well as using the Autor and Dorn (2013) occupation classification.

The results of this appendix show that exposure to technological change does not impact the probability of being employed after displacement or the probability of exiting the labor market after displacement.

Table A16: Technological change and employment after displacement

Dependent variable: indicator for being employed after displacement

	(1)	(2)	(3)
Chg. Computer Req.	0.00503	0.00648	0.000471
	(0.00918)	(0.00809)	(0.00710)
Chg. Emp. Share		0.0168**	0.0100**
		(0.00650)	(0.00478)
Observations	10,519	10,519	10,519
R-squared	0.134	0.135	0.134
Controls	Yes	Yes	Yes
Occ. Def.	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 employed after displacement. 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, 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, and an indicator for working full-time prior to displacement. 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.

Table A17: Technological change and exiting labor force after displacement

Dependent variable: indicator for not being in labor force after displacement			
	(1)	(2)	(3)
Chg. Computer Req.	-0.00132	-0.00152	-0.00106
	(0.00138)	(0.00144)	(0.00117)
Chg. Emp. Share		-0.00240**	-0.000737
		(0.000973)	(0.000968)
Observations	10,519	10,519	10,519
R-squared	0.009	0.010	0.009
Controls	Yes	Yes	Yes
Occ. Def.	SOC-4	SOC-4	SOC-4

Notes: The table shows regression results from the estimation of equation 1, where the dependent variable is an indicator for not begin in the labor force after displacement. See notes to Table A16 for list of control variables. 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.

C.11 Additional Results

C.11.1 Earnings losses after displacement

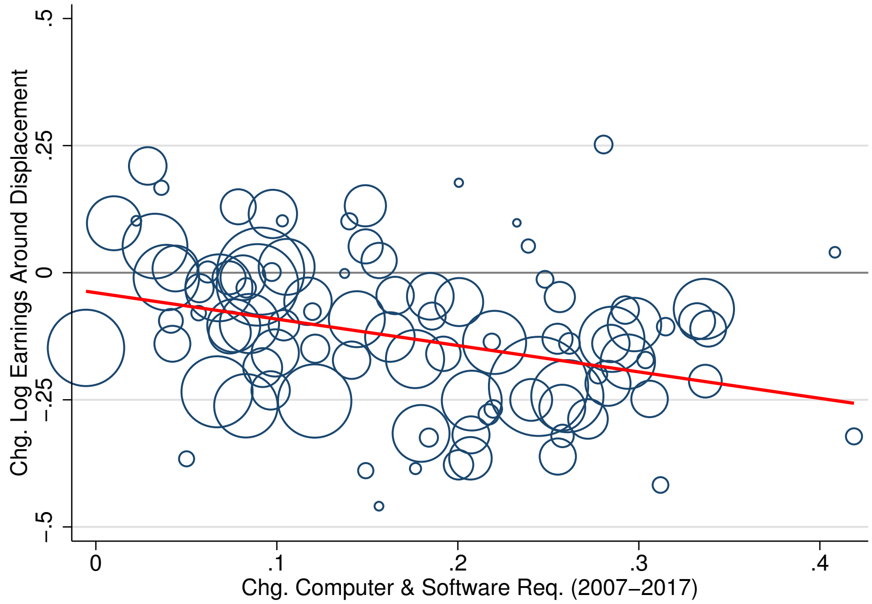
In Figure A11, we present a scatter plot of the change in computer and software requirements by four-digit SOC code on the x-axis and the average change in log earnings around displaced by occupation on the y-axis. The size of each circle corresponds to the relative employment share of the occupation in 2007. The red lines represents a linear trend line between the change in computer and software requirements in an occupation and the average size of earnings losses. The figure shows that occapations more exposed to technological change see a larger decline in earnings after job loss, on average.

C.11.2 Geographic variation in exposure to technological change

In this appendix, we examine the sensitivity of our results to exploiting geographic variation in the exposure of an occupation to technological change as measured by changes in computer and software requirements. We find that our results are largely unchanged by incorporating geographic variation in exposure to technological change on the outcomes of displaced workers.

We first briefly describe our measure of exposure to technological change which exploits geographic variation. As in Appendix B.4, let $z_{o,s,t}$ denote the share of vacancies in occupation o, state s, and year t that contain a computer or software related skill. We measure the exposure

Figure A11: Technological change and earnings losses after displacement by occupation



Note: The figure shows 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). The size of each circle corresponds to its employment share in the 2007 ACS. Occupations are classified using four-digit SOC codes.

of occupation o in state s to technological change by defining $\Delta z_{o,s} = z_{o,s,2017} - z_{o,s,2007}$.[26]

We next discuss how we use this measure of technological change, which incorporates geographic variation. Let $Y_{i,o,s,t}$ denote the outcome variable of interest for individual i living in state s, who was displaced in occupation o and is in the DWS in year t (e.g., the change in log real earnings following displacement, etc.).[27] Let $\Delta z_{o,s}$ denote the change in the share of vacancies listing computer or software requirements for occupation o between the years 2007 and 2017 in state s, which has been normalized to be mean zero and have unit standard deviation. Let $X_{i,s,o,t}$ denote a vector of controls, which includes the change in the employment share of occupation o in state s 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, and years of educational attainment, as well as a series of dummy variables including 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. Finally, let γ_s denote a set of state fixed effects.

[26] Appendix B.4 presents measures on the degree of geographic variation in exposure to technological change.

[27] For this analysis, we restrict our sample to individuals who have not moved since layoff since we obtain their location based upon their current CPS observation. This decreases the sample size by approximately 14%. We do not find that *moovers* have different earnings losses or propensities to switch occupations relative to non-moovers.

The specification we use is of the form

$$Y_{i,o,s,t} = \alpha + \beta \Delta z_{o,s} + \Gamma X_{i,o,s,t} + \gamma_s + \epsilon_{i,o,s,t}. \tag{3}$$

We will use equation 3 to examine how exposure to technological change impacts the the outcomes of displaced workers.

In the first column of Table A18 we present the results of estimating equation 3 where the dependent variable is the change in log earnings around layoff. The negative and statistically significant coefficient indicates that workers displaced from occupations undergoing larger increases in computer and software requirements (in their state) experience a larger decline in earnings following displacement. In column (2) of Table A18 we present the results of estimating equation 3 where the dependent variable is an indicator for switching occupations following displacement. The positive and statistically significant coefficient indicates that workers with greater exposure to technological change are more likely to switch occupations following displacement. Finally, in columns (3) and (4) we examine how exposure to technological change impacts the length of an individuals unemployment spell following displacement (column (3)) and their probability of being employed at the time of the DWS survey (column (4)). We find that greater exposure to technological change *does not* impact the length of an indviduals unemployment spell and does not impact their probability of being employed at the time of the DWS survey.

C.11.3 Loss of full-time work after displacement

In this appendix, we examine if exposure to technological change impacts the probability of losing full-time work after displacement. We find that workers more exposed to technological change are *less* likely to lose full-time work after displacement. This further suggests that the larger earnings losses for workers more exposed to technological change is due to declines in wages rather than hours.

Table A19 presents the results of estimating equation 1 where the dependent variable is an indicator for losing full-time work after displacement. For the results presented in Table A19 we limit the sample to workers who are employed in full-time work prior to displacement and employed after displacement. The negative and statistically significant coefficient on the change in computer and software requirements in column (1) of Table A19 suggests that workers more exposed to technological change are less likely to lose full-time work after displacement. In column (2) of Table A19 we show that we obtain similar results controlling for the change in employment share in the individuals occupations. Finally, in column (3) we find some support

Table A18: Outcomes of displaced workers and technological change by state

	(1) Chg. Log Real Earnings	(2) Switch Occ. (d)	(3) Unemp. Dur	(4) Emp. (d)
Chg. Computer Req.	-0.0307***	0.0680***	0.376	0.00134
	(0.0106)	(0.0204)	(0.410)	(0.00699)
Observations	5,838	5,838	5,838	9,276
R-squared	0.249	0.045	0.124	0.147
Controls	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Sample	Emp. Sample	Emp. Sample	Emp. Sample	Pop. Sample
Occ. Def.	SOC-4	SOC-4	SOC-4	SOC-4

Notes: This table shows regression results from the estimation of equation 3. 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 and state the worker was displaced from, years of educational attainment, and the change in ACS employment share between 2007 and 2017 in the occupation and state from which an individual was displaced 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. The symbol (d) indicates a dummy variable. Earnings are measured as the difference in log real earnings, where earnings are measured in 2012 dollars. Occupation switching is defined using four-digit SOC codes. The employed sample (columns (1)-(3)) refers to individuals in the DWS who are employed both prior to and after displacement, while the population sample (column (4)) is all individuals who are employed prior to displacement. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

for this phenomenon using the occupation classification from Autor and Dorn (2013) (p-value = 0.08). Given that we have found that workers more exposed to technological change suffer larger earnings losses, the results of Table A19 suggest that these larger earnings losses are due to declines in wages rather than declines in hours.

C.11.4 Alternative weights

In this appendix, we show that our results on the impact of exposure to technological change on the size of earnings losses are robust to alternative sampling weights. In the empirical analysis of Section IV we weight all regressions and summary statistics using the sample weights for the DWS provided by IPUMS. In this appendix, we show that we obtain similar results using alternative weights. Table A20 presents the results of estimating equation 1 where the dependent variable is the change in log earnings after displacement using alternative sampling weights. In columns (1) of Table A20 we present our baseline results which use the DWS sam-

Table A19: Technological change and losing full-time work

Dependent variable: indicator for losing full-time job			
	(1)	(2)	(3)
Chg. Computer Req.	-0.0357***	-0.0374***	-0.0160*
	(0.00981)	(0.00953)	(0.00912)
Chg. Emp. Share		-0.0177***	-0.00777
		(0.00535)	(0.00548)
Observations	5,786	5,786	5,786
R-squared	0.031	0.032	0.028
Controls	Yes	Yes	Yes
Occ. Def.	AD	AD	AD

*Notes: This table shows regression results from the estimation of equation 1 where the dependent variable is an indicator for losing full-time work after displacement. We limit the sample to only include workers employed full-time prior to displacement and employed after displacement. 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, and the year of displacement. Clustered standard errors are in parentheses, where the clustering is performed at the occupation level. Occupations are classified using four-digit SOC codes in columns (1) and (2), while occupations are classified using Autor and Dorn (2013) occupation codes in columns (3). ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.*

pling weights.[28] In column (2) of Table A20 we weight individuals by the 2007 ACS employment share in the occupation from which they were displaced. In column (3) of Table A20 we use the final person level weight from the basic monthly CPS file.[29] Finally, in column (4) of Table A20 we do not use any sampling weights. The coefficient estimates in Table A20 show that we obtain very similar results using alternative sampling weights, or not weighting at all. In results available upon request, we also find that the choice of sampling weights do not substantially alter our estimates on the impact of technological change on other outcomes after displacement (e.g., switching occupations after displacement.).

D Quantitative model additional details

In this appendix, we present additional details of the model. We first present the value functions for experienced workers, as well as firms. We then present the government's budget constraint and formally define equilibrium.

[28] In IPUMS, this is variable "dwsupwt."

[29] In IPUMS, this is variable "wtfinl."

Table A20: Technological change & earnings losses after displacement: alternative weights

Dependent variable: change in log earnings after displacement

	(1)	(2)	(3)	(4)
Chg. Computer Req.	-0.0345***	-0.0373***	-0.0343***	-0.0425***
	(0.0122)	(0.0118)	(0.0121)	(0.0114)
Observations	6,742	6,742	6,742	6,742
R-squared	0.234	0.245	0.234	0.233
Controls	Yes	Yes	Yes	Yes
Occ. Def.	SOC-4	SOC-4	SOC-4	SOC-4
Weight	DWS Weight	2007 ACS Emp.	CPS Final Weight	No Weight

Notes: This table shows regression results from the estimation of equation 1 where the dependent variable is the change in log earnings after displacement. 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. Occupations classified using four-digit SOC codes. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

D.1 Bellman equation for unemployed experienced worker

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

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

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

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

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

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

$$h^{'} = H(h).$$

D.2 Bellman equation for employed experienced worker

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

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

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

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

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

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

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

D.3 Firms matched with a worker and free entry

In this section we present the firm bellman equations as well as the free-entry condition.

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

If the worker does not match with another job via on-the-job search, then the match continues and the firm continues to receive the benefits of the match. The probability that the worker leaves the firm via on-the-job search depends on where the worker searches for a new match in the next period. Let $y = (t,h,z,x,k,\omega)$ denote the state of the individual that the firm is matched with in the current period. Let $y' = (t+1,h',z',x',k,\omega)$ denote the agent's state in the next period when making their decision about which occupation and wage piece rate to search for a job in (i.e., after shocks to human capital, match technology, and experience are realized). Let $\hat{k}(y')$ denote the occupation where the worker searches for a job, and let $\hat{\omega}(y')$ denote the wage piece rate where the worker searches for a job. With probability $p(\theta_{t+1}^{x(\hat{k})}(h',\hat{k}(y'),\hat{\omega}(y')))$ the worker matches with another job via on-the-job search.[30] The value to the firm is given by

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

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

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

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

Firm matched with experienced worker. We next present the Bellman equation for a firm that is matched with an experienced worker. Let $J_t^E(h,z,k,\omega)$ denote the value to a firm in occupation k of being matched with an experienced worker with human capital h, using technology

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

$z \leq \bar{z}$ where the worker is paid piece rate ω. In the current period, the firm produces and makes wage payments. In the next period, the match can expire due to an exogenous separation, or the worker leaving due to on-the-job search. If the match continues, the firm continues to receive the benefits of the match. The value to the firm is given by:

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

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

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

Vacancies. Potential firms enter the market and post vacancies to hire an age t worker with experience $x \in \{E, N\}$, and human capital h, and for occupation k at wage piece-rate ω subject to the free-entry condition

$$
\kappa \geq p_f(\theta_t^x(h,k,\omega)) J_t^x(h, \bar{z}, k, \omega) \quad \text{for } x \in \{E, N\}, \tag{4}
$$

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

D.4 Equilibrium

A recursive competitive equilibrium for this economy is a list of household policy functions for wage search $\{\hat{\omega}'_{e,x,t}(h,z,k,\omega)\}$, occupation search $\{\hat{k}_{e,t}^x(h,z,k,\omega)\}$, a labor market tightness function $\{\theta_t^x(h,a,k,\omega)\}$, and a distribution of individuals across states Ω such that

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

2. The labor market tightness in each occupation is consistent with the free-entry condition in equation 4.

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

D.5 Solution algorithm

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

1. **Firms Bellman:** Compute the value to a firm of being in a match in the terminal period $J_T^x(h, a, \bar{z}, k, \omega)$ at the value of the frontier technology.[31] Using the value of a firm in the terminal period, invert the free entry condition to obtain labor market tightness $\theta_T^x(h, a, k, \omega)$.

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

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

4. **Simulation:** Simulate a mass of individuals to get steady state distribution of agents. [32]

D.6 Calibration details

In this appendix we provide additional details on the calibration of the model that was presented in Section V.C.

D.6.1 Model fit

Table A21 contains a summary of the model parameters, and Table A22 displays the calibrated parameters and their calibration targets.

D.6.2 Calibration of Technology Parameters

In this section, we provide additional details on the calibration of the technology intensity parameters of the model ($\{c_k\}$). Calibrating the technology intensity parameters proceeds in two

[31]Not we measure the value at the frontier technology because all matches are formed at the frontier technology in an occupation.

[32]We simulate 50,000 individuals for 260 periods, burning the first 120 periods.

Table A21: Model parameters

	Non-estimated	
Variable	Value	Description
g	1.5%	Annual technology growth rate
ι	0.25%	Quarterly probability of technology decay
r	0.04	Risk-free rate
β	0.99	Worker's discount factor
δ	0.1	Exogenous job destruction rate
A_N	1.00	Inexperienced worker productivity
A_E	1.12	Experienced worker productivity
λ_E	0.05	Probability of becoming experienced
ξ	1.6	Labor search match elasticity
T	120	Life span in quarters
	Jointly estimated	
Variable	Value	Description
b	0.245	Public insurance transfer to unemployed
κ	0.323	Firm entry cost
λ_N	0.892	Probability of becoming inexperienced when unemployed
λ_H	0.314	Exponential parameter for initial human capital
c_1	0.553	Technology intensity 1st occupation
c_2	0.579	Technology intensity 2nd occupation
c_3	0.605	Technology intensity 3rd occupation
c_4	0.642	Technology intensity 4th occupation
c_5	0.672	Technology intensity 5th occupation
c_6	0.704	Technology intensity 6th occupation
c_7	0.729	Technology intensity 7th occupation
c_8	0.753	Technology intensity 8th occupation
c_9	0.793	Technology intensity 9th occupation
c_{10}	0.881	Technology intensity 10th occupation

Table A22: Model calibration

Var.	Value	Target	Model	Data	Source
b	0.245	Transfer to Income Loss	41.4%	41.2%	PSID
κ	0.323	Unemployment Rate	6.8%	6.8%	BLS
λ_N	0.892	Share Switching Occ. After Layoff	51.3%	62.0%	CPS
λ_H	0.314	P75-P25 Log Residual Earnings of Young Workers	0.305	0.381	CPS
c_1	0.553	Ratio of Occ. Earnings / Avg. Earnings	0.800	0.793	CPS
c_2	0.579	Relative Earnings 2nd Occupation	1.064	1.048	CPS
c_3	0.605	Relative Earnings 3rd Occupation	1.118	1.113	CPS
c_4	0.642	Relative Earnings 4th Occupation	1.182	1.184	CPS
c_5	0.672	Relative Earnings 5th Occupation	1.249	1.248	CPS
c_6	0.704	Relative Earnings 6th Occupation	1.322	1.311	CPS
c_7	0.729	Relative Earnings 7th Occupation	1.365	1.368	CPS
c_8	0.753	Relative Earnings 8th Occupation	1.411	1.414	CPS
c_9	0.793	Relative Earnings 9th Occupation	1.505	1.500	CPS
c_{10}	0.881	Relative Earnings 10th Occupation	1.691	1.684	CPS

steps: (1) assigning each four-digit occupation to one of 10 occupation groups, and (2) measuring earnings across the 10 occupation groups. Using estimates of earnings across the 10 occupation groups we calibrate the parameters ($\{c_k\}$).

First, we partition the distribution of occupations (in the data) into $K = 10$ groups based on the share of vacancies listing a computer or software requirement in 2010. The groups are formed by evenly spacing grid points in terms of the share of vacancies listing a computer or software requirement in 2010. Table A23 contains the grid points that are in each group. Let $k \in \mathcal{K} = \{1, 2, .., 10\}$ denote an occupation group, and let o denote an occupation at the four-digit SOC code level.

Second, we measure earnings across the occupation groups k. Let $e_{i,o,t}$ be the real earnings of individual i working in occupation o in period t, let $z_{o,2010}$ denote the share of vacancies listing a computer or software requirement in occupation o in the year 2010, and let γ_t denote a set of year dummy variables. We estimate the following regression of computer and software requirements on earnings using data from the CPS:[33]

$$e_{i,o,t} = \alpha + \beta z_{o,2010} + \gamma_t + \epsilon_{i,o,t} \tag{5}$$

Using the coefficients from the estimation of equation 5, we compute the predicted earnings

[33] In estimating equation 5 we use the outgoing rotation groups of the monthly CPS survey between 2010 and 2017. Earnings are measured as real weekly earnings. To ensure a minimum degree of labor force attachment, we remove individuals with real weekly earnings below $100.

Table A23: Occupation groups and cutoffs

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

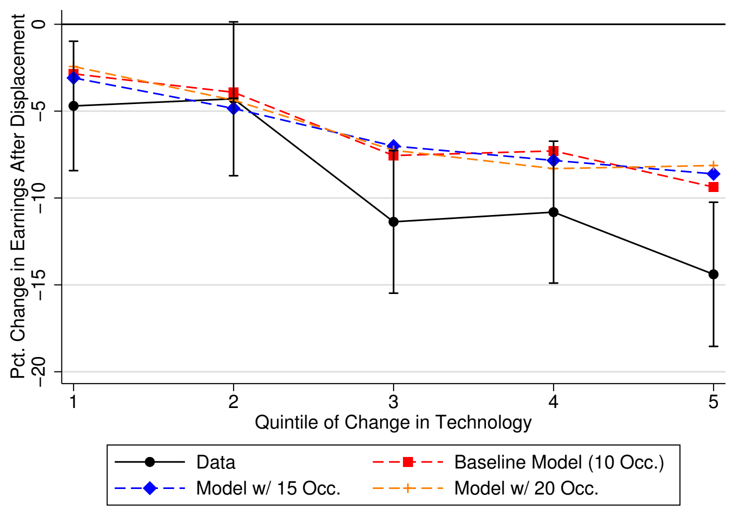
Notes: Table shows the cutoffs used to form the 10 occupation groups in the data. four-digit occupations are placed into one of the 10 occupation groups based on the share of vacancies listing a computer or software requirement in 2010.

for each individual. Let $\hat{e}_{i,o,t}$ denote the predicted earnings for individual i working in occupation o in year t. From these predicted values we estimate average predicted earnings for each occupation group $k \in \mathcal{K}$, which is denoted by $\bar{e}_k$. We use the set of smoothed earnings $\bar{e}_k$ to govern the technology parameters in the model. We calibrate the technology intensity of the first occupation (c_1) to match the ratio of smoothed earnings in the first occupation to average earnings among all workers. We calibrate the remaining technology parameters ($\{c_k\}_{k=2}^{k=10}$) to match the ratio of smoothed earnings in occupation k relative to the first occupation ($\frac{\bar{e}_k}{\bar{e}_1}$). Table A22 contains the parameter estimates of the technology intensity parameters as well as their model fit.

D.6.3 Calibration of model without technological change

In this section, we discuss the estimation of the model without technological change ($g = 0\%$). In estimating the model without technological change we keep all parameters fixed from the baseline estimation. However, technological change impacts the distribution of workers general human capital in the model. To make the distribution of human capital consistent across estimations of the model in the model without technological change individuals draw their human capital from the stationary distribution of human capital from the baseline version of the model.

Figure A12: Robustness: earnings losses by number of occupations



Note: The figure shows the size of earnings losses by quintile of change in technology in the data (black, solid line), baseline model (red line, with square markers), model with 15 occupations (blue line with diamond markers) and 20 occupations (orange line, with + markers).

D.7 Robustness: number of occupations

In this appendix, we examine the robustness of the quantitative model's predictions for the outcomes of displaced workers to the number of occupation used in the quantitative model. We find that the predictions of the quantitative model are robust to the number of occupations used.

In Figure A12 we plot the size of earnings losses in the baseline model, which includes 10 occupations (red line, with square markers), as well as from the quantitive model with 15 occupations (blue line, with diamond markers) and 20 occupations (orange line, with + markers) by the quintile of exposure to technological change in the occupation they were displaced from.[34] The figure shows that we obtain very similar predictions on the size of earnings losses across occupation exposure quintiles. Hence, the number of occupations does not play a substantial role in the size of earnings losses in the quantitative model. The intuition for this result is that with more occupations, individuals are more likely to switch occupations after displacement, but the size of the fall down the technology ladder is smaller. Quantitatively, these forces balance out.

We next examine the robustness of our results on the decomposition of earnings after displacement. Table A24 presents the results of the decomposition exercise for estimations of the

[34]To add occupations into the quantitative model we use the grid of occupation cutoffs from Appendix D.6.2. We then identify the 5 pairs of occupations with the largest gap in technology intensity parameters c_k. We then add an occupation at the midpoint of each of these pairs. We repeat this process again to go from 15 to 20 occupations.

model with different numbers of occupations. In Panel (A) of Table A24 we show that we obtain similar sizes of earnings losses in the full model with 10, 15, and 20 occupations. Additionally, we find similar earnings losses with different numbers of occupations in the quantitative model when technological change is removed from the model as well as when experience (occupation-specific human capital) is removed. In Panel (B) of Table A24 we show the share of earnings losses after displacement attributable to different features of the model by the number of occupations. In the baseline estimation with 10 occupations, 45.5% of earnings losses are due to technological change. With 15 and 20 occupations in the quantitative model, we find that technological change accounts for 43.3% and 42.8% of earnings losses respectively. Hence, the number of occupations does not change our finding that technological change plays a central role in shaping earnings losses after displacement.

Table A24: Robustness of earnings decomposition

Panel (A): *Size of earnings losses*			
	(1)	(2)	(3)
	Baseline (10 Occupations)	15 Occupations	20 Occupations
Full Model	-7.63%	-7.69%	-7.54%
W/o Tech. Change	-4.16%	-4.36%	-4.31%
W/o Tech. Change & Exp.	-1.53%	-1.53%	-1.70%
Panel (B): *Share of earnings losses attributable to factor*			
	(1)	(2)	(3)
	Baseline (10 Occupations)	15 Occupations	20 Occupations
Technological Change	45.5%	43.3%	42.8%
Occ. Specific Human Capital	34.5%	36.8%	34.7%
Wage Ladder	20.0%	19.9%	22.5%

Notes: Table shows the size of earnings losses across different estimations of the model and with different numbers of occupations. Panel (a) presents the size of earnings losses across these estimations. Panel (b) provides the decomposition of the share of earnings losses attributable to different features of the quantitative model.

E Evidence from SSA-ASEC earnings records

In this appendix, we use a linked sample of earnings records from the Social Security Administration (SSA) and the Current Population Survey Annual Social and Economic Supplement (ASEC) to examine the role of exposure to technological change on the outcomes of workers after layoff. The SSA-ASEC sample is a panel data set of individual earnings histories supplemented with additional information on an individual's labor market experiences, and importantly for this paper contains information on occupation. The panel nature of the data set extends the analysis presented in Section IV by allowing us to examine the path of earnings following layoff, and how the path of earnings losses is impacted by exposure to technological change. Additionally, this exercise allows us to consider a broader sample of unemployment spells and not only displaced workers.[35] We find that exposure to technological change lowers the path of earnings following layoff for at least the first five years after layoff. Consistent with the empirical evidence from Section IV and Model Prediction 3 in Section I, the larger earnings losses in response to technological change is concentrated among occupation switchers.

Background on SSA-ASEC earnings records

In this appendix, we use a linked sample of earnings records from the Social Security Administration and the ASEC. The SSA provides us with job level W2 earnings for each year an individual registers W2 income between 1976 and 2016. Using scrambled social security numbers, we are able to supplement the SSA earnings data with survey responses from the ASEC. The ASEC asks a series of questions about an individual's labor market experience in the prior year, and central for this paper inquires about the number of weeks on layoff as well as primary occupation.[36] The sampling structure of the ASEC makes it so that individuals are typically in the ASEC in two consecutive years, so it is possible to see an individual enter into unemployment and/or switch occupations across ASEC surveys. When we combine these databases, we obtain a sample with two years of detailed information from the ASEC (e.g., weeks on layoff and occupation) and a full time series of an individual's annual labor earnings from the SSA.[37]

Sample construction

Using the SSA-ASEC data we construct a panel of laid off and non-laid off workers. We identify a worker to have been *laid off* in year t if they report having positive weeks on layoff in year t, and report zero weeks on layoff in year $t-1$. We impose the requirement that an individual have zero weeks on layoff in year $t-1$ so that we are able to accurately measure the inflow of individuals into unemployment. We classify workers as *non-laid off* if they report having zero weeks on layoff in both year t and in year $t-1$. To align with the time period we have the Burning Glass database we only consider workers who have been laid off (or alternatively, not laid

[35]As we will discuss below, our treatment group in this Appendix will be individuals with positive weeks on layoff in their second ASEC wave. In Section IV, we considered displaced workers which required that a worker lost their job because of their company or plant shutting down, their shift or position being eliminated, or their firm having insufficient work.

[36]On their own administrative earnings databases for the U.S. such as the SSA data and the LEHD do not contain information on occupation.

[37]For more information on the SSA-ASEC sample see Braxton, Herkenhoff, Rothbaum, and Schmidt (2021).

Table A25: Summary statistics ASEC-SSA earnings histories

	(1) Treatment	(2) Control
Chg. Computer Req.	0.168	0.182
Real Annual Earnings	\$46,870	\$63,490
Age	40.63	43.53
Share with college degree	0.264	0.386
Avg. weeks on layoff	17.78	-
Share switching occupations	0.651	0.429
Observations	8,000	166,000

Notes: Column (1) displays summary statistics for the treatment group of laid off individuals, while column (2) displays summary statistics for the control group of non-laid off individuals. The change in computer and software requirements is measured between 2007 and 2017 in the occupation the indiviudal was laid off from (column (1)) or not laid off from (column (2)). Summary statistics on real annual earnings, age, and education are from the year before layoff (or non-layoff). Earnings are measured in 2019 dollars. Occupation switching is measured using four-digit SOC codes.

off) between 2007-2015.[38] Additionally, for individuals who report positive weeks on layoff in year t, we use their primary occupation in year $t-1$ as reported in the ASEC as the occupation they were laid off from.[39] It will be in this occupation that we use changes in computer and software requirements to estimate the individual's exposure to technological change.

From this sample of laid off and non-laid off individuals we define our treatment and control groups. To be in the treatment group, we require a laid off workers to: (1) have earnings above a minimum earnings cutoff in the year prior to layoff, and in at least three out of the five years prior to layoff, and (2) to have earnings above the minimum earnings cutoff in at least one year after layoff.[40] These additional sampling requirements are common in the displaced worker literature, and help to ensure a minimum amount of labor force attachment prior to layoff and to insure that the earnings losses are not being driven by individuals who completely exit the labor market (e.g., due to retirement). To align treatment and control groups, we impose the same requirements on non-laid off workers to be in the control group. This sampling procedure results in a sample of 8,000 laid off workers and 166,000 non-laid off workers. Table A25 reports summary statistics for these samples.[41]

[38] Recall that our sample of earnings histories from the SSA end in 2016. To have one year of post layoff earnings, the last year we consider for being laid off is 2015.

[39] We classify occupations using four-digit SOC codes.

[40] We set the minimum earnings cutoff to \$5,200 to be consistent with the minimum earnings threshold used in the DWS samples in Section II.B.

[41] To comply with Census Bureau disclosure results, sample sizes are rounded to the nearest thousand and all estimates are rounded to four significant digits.

Empirical approach.

In this section we discuss our empirical approach for measuring the impact of exposure to technological change on the path of earnings following layoff.

To benchmark our results on the role of exposure to technological change on the outcomes of laid off workers we start by examining the average response of earnings following layoff. Let i index individuals and t index years. Let α_i denote a set of individual fixed effects and γ_t denote year dummies. Let $Y_{i,t}$ denote real earnings of individual i in year t. Let $D_{x,i,t}$ be a dummy variable taking the value 1 when an individual is x years before (if x is negative) or after (if x is positive) layoff. For example, $D_{-1,i,t}$ is a dummy variable indicating an individual is 1 year before layoff. The vector $X_{i,t}$ contains control variables, in particular deciles of lagged cumulative earnings interacted with year fixed effects. The specification we use is of the following form:

$$Y_{i,t} = \alpha_i + \gamma_t + \sum_{j=-4}^{5} \beta_j D_{j,i,t} + \Gamma X_{i,t} + \varepsilon_{i,t} \tag{6}$$

The objects of interest are $\{\beta_j\}_{j=0}^{5}$, which summarize the impact of layoff on the outcome variable in the year of layoff and subsequent years. To examine the validity of the point estimates, we test that the treatment and control groups have parallel trends prior to layoff (i.e. $\beta_{-4}, .., \beta_{-1}$ are not statistically different from zero).

Panel (a) of Figure A13 plots the implied path of earnings following layoff based on the results of estimating equation 6. The figure shows that being laid off causes a large and persistent decline in earnings, which has been shown in many previous papers (e.g. Jacobson et al. (1993), Couch and Placzek (2010), and Davis and von Wachter (2011) among others). In the next section, we examine the role of exposure to technological change in shaping the path of earnings following layoff.

Exposure to technological change.

We next examine the role of exposure to technological change in shaping the path of earnings for laid off workers. Let Δz_o denote the change in computer and software requirements in occupation o between 2007 and 2017.[42] Let $Y_{i,o,t}$ denote the real annual earnings of individual i in year t, who was laid off from occupation o.[43] The specification we use is of the form:

[42] The change in computer and software requirements is measured by four-digit SOC code and for the occupation from which an individual was laid off.

[43] In the case of the control group, occupation o is their first ASEC occupation from which they were not laid off.

$$Y_{i,o,t} = \alpha_i + \gamma_t + \sum_{j=-4}^{5} \beta_j D_{j,i,t} + \sum_{j=-4}^{5} \eta_j (D_{j,i,t} \times \Delta z_o) + \Gamma X_{i,t} + \varepsilon_{i,o,t} \tag{7}$$

The coefficients of interest are $\{\eta_j\}_{j=0}^{5}$, which report the impact of exposure to technological change on the path of earnings after layoff. If $\eta_j < 0$, then greater exposure to technological change in the occupation from which an individual is laid off is associated with lower earnings in period j. Additionally, the coefficients $(\eta_{-4}, ..., \eta_{-1})$ test if outcomes prior to layoff differ by the change in computer and software requirements in the occupation from which an individual is laid off.

To visualize the results, we present the implied path of earnings for individuals laid off in an occupation with no change in computer and software requirements and individuals laid off at the mean of the change in computer and software requirements. Panel (b) of Figure A13 shows the path of earning for individuals laid off at the mean change in computer and software requirements (black, dashed line) and zero change in computer and software requirements (red, solid line).[44] The figure shows that individuals laid off at the mean change in computer and software requirements have a persistently lower path of earnings following displacement relative to individuals laid off from an occupation with zero change in computer and software requirements. On average, individuals laid off at the mean have earnings that are \$3k lower per year following displacement relative to individuals laid off from an occupation with no change in computer and software requirements. Hence, exposure to technological change puts individuals on a lower path of earnings for at least 5 years after layoff.

As another way to examine the role of technological change in shaping earnings losses after displacement, we can use the results from estimating equation 7 to compute the present-discounted value (PDV) of earnings losses for individuals by their exposure to technological change. We compute the present discounted value of earnings losses over the first 5-years after layoff as a function of exposure to technological change using,

$$PDV(\Delta z_0) = \sum_{j=0}^{5} \frac{\beta_j + \eta_j \Delta z_0}{(1+r)^j}$$

where β_j and η_j are the coefficients from estimating equation 7, and r is the interest rate, which we set to 5% as in Davis and von Wachter (2011). For individuals who are laid off from an occupation with zero change in computer and software requirements, the PDV of earnings losses is nearly \$25k (\$24,733.57). Conversely, for individuals laid off from an occupation at

[44] The dotted black line is a 95 percent confidence interval around the path of earnings at the mean change in computer and software requirements. Standard errors are clustered at the individual level.

the mean change in computer and software requirements, the PDV of their earnings losses is over \$40k (\$40,892.10).[45] Hence, exposure to technological change prior to layoff results in a substantially larger decline in earnings after displacement.

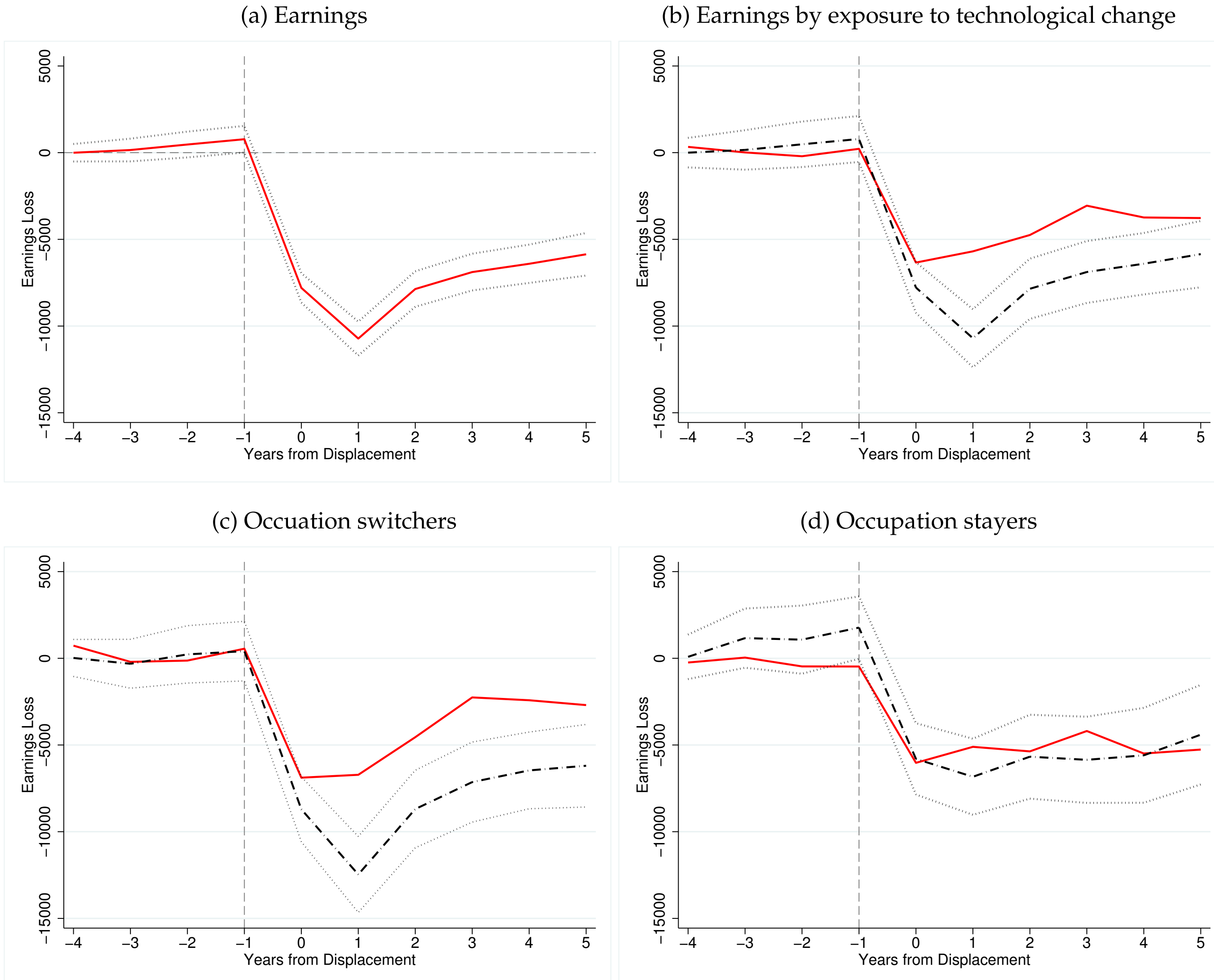
Finally, we examine the mechanism through which changes in computer and software requirements impact earnings after layoff. The simple model from Section I and the results in Section IV highlighted occupation switching as playing a central role in exposure to technological change contributing to lower earnings after layoff. We define an individual to have switched occupations if their current occupation in their second ASEC wave is different from their ASEC occupation in the first ASEC wave.[46] We separately estimate equation 7 for individuals who switch occupations following displacement and individuals who do not switch occupations following layoff.

Panel (c) of Figure A13 shows the path of earnings for individuals who switch occupations following displacement by the change in computer and software requirements in the occupation they were laid off from. The figure shows that individuals laid off from occupations at the mean of the change in computer and software requirements have a significantly lower path of earnings in every year following displacement relative to individuals laid off from an occupation with zero change in computer and software requirements. Panel (d) of Figure A13 shows the path of earnings for individuals who did not switch occupations following displacement. The figure shows that for each year after layoff individuals who regained employment in their original occupation did not experience a significantly different earnings path based upon their exposure to technological change prior to layoff. We interpret the results of Panel (c) and (d) of Figure A13 as providing evidence that occupation switching is the mechanism through which exposure to technological change lowers the path of earnings after layoff.

[45] As reported in our Table A25, the average change in computer and software requirements for the SSA-ASEC sample is 0.168.

[46] We measure occupation switching using four-digit SOC codes. Table A25 reports that among the treatment group 65.1% of individuals switch occupations after layoff, while 42.9% of individuals in the control group switch occupations.

Figure A13: Technological change and the path of earnings after layoff



Note: Figure presents the coefficient estimates from estimating equation 6 (Panel (a)) and equation 7 (Panels (b)-(d)). Earnings are measured in 2019 dollars. In panels (b)-(d) the red line represents the path of earnings for workers laid off from an occupation with no change in computer and software requirements, and the black, dashed, line represents the path of earnings for an individual laid off from an occupation at the mean change. Finely dashed lines represent a 95% confidence interval. Panels (a) and (b) include the full sample of laid off workers. In Panel (c) we only include laid off workers who switched occupations and in panel (d) we only include only occupation stayers. In all panels, we use the full sample of non-laid off workers as a control group.

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