1 Empirical Analysis

This appendix presents additional empirical results that complement those presented in Section 6 of the paper. Section 1.1 discusses details about the data construction procedure. Section 1.2 reports the summary statistics of our baseline sample. Section 1.3 presents additional empirical results that attest the robustness of the estimates presented in Section 6.2 of the paper.

1.1 Data construction

The raw data in the LIAB comes in the form of entire job histories of workers in the sample. Individual entries therefore contain worker information, as well as information on the start and end date of a job spell for that individual, the location (establishment), and characteristics of the job spell. We transform this data into an annual panel dataset following the steps in Card et al. (2013), with minor modifications. Specifically, we sequentially restrict our sample by selecting (i) males in West Germany, (ii) those aged 15-64 years at the time of the job spell, and (iii) the job-spell within a calendar year with maximum earnings. We then adjust wages by (i) deflating earnings using German CPI information from FRED (Series A0000178NEX4.}}
id: DEUCPIALLMINMEI) and (ii) replacing daily wages with Upper Earnings Limits in Card et al. (2013) for daily wages above censor limit. Finally, we impute each individual’s district of employment using the district of the establishment of the individual’s main job in each year. Since this information only exists after 1999, we assign the establishment’s district in 1999 to 1995-1998.

While the years represented in our data and our underlying data sample differ from those of Card et al. (2013), our panel well represents the data used in that paper. Figure 1.1 shows that the mean wage changes of job movers, classified by the mean log wages of coworkers in their old and new establishments, is similar in our data to the main findings in Card et al. (2013) (their Figure Vb).

We also link our LIAB-based worker panel to the DSL access data from Falck et al. (2014) using the district identifiers in both datasets. We then construct the instrumental variables discussed in Section 6.2 of the paper. Figure 1.2 illustrates the spatial variation of the instruments used to estimate our baseline results.

Figure 1.1: Replication of Card et al. (2013)

Note. Figure illustrates the mean wage changes for job movers from the fourth and first quartile of establishments in all quartiles of establishments. Movers are defined as workers who move jobs from a job they held for two years before moving, and stay in the new job for two years after moving. Quartiles are defined by the mean log wages of coworkers in the old and new establishments. The sample period is 2002-2009. transi = 3 is the year of moving.
Figure 1.2: Spatial Variation in the Instrumental Variables

Note. Panel A illustrates the number of municipalities across districts in Germany that did not have access to an MDF within the 4200m radius ("MDF Density Measure"), as described in Section 6.2. Panel B illustrates the number of municipalities across districts that did not have their own MDF and did not have access to an alternative MDF in a neighboring district "Alternative MDF Availability".
1.2 Sample statistics

This section reports the summary statistics of our baseline sample. We first focus on the increase in inequality, measured by the standard deviation of log wages, in our sample. Figure 1.3 compares the overall change in inequality together with the between district-generation-occupation component, which we measure using the residual log-wage dispersion from a mincer regression including dummies for the district-generation-occupation estimated for each year. Between 1997-2012, overall inequality in our sample increased by about 8.5 log points. Moreover, the between district-generation-occupation component explains about half of the increase in inequality during this period. In results available on request, we attest that each of these characteristics alone does not account for the inequality rise.¹

Table 1.1 presents summary statistics underlying the FDZ microdata used in our empirical analysis. They illustrate the evolution of the number of employees, ages and log-wage of the baseline generations used in estimation.

Figure 1.3: Aggregate Trends in Log Wage Variance

Note: Estimation of the aggregate standard deviation of log wages on the full LIAB sample and the residual dispersion in log wages from a mincer regression including district-occupation-generation dummies. Estimates are changes in dispersion relative to 1999.

¹We also attest that the explanatory power of the between district-generation-occupation component is similar to that of the between establishment component of log-wage variance, which Card et al. (2013) point as the main driver of the inequality increase in Germany during this period. Notice that this is not mechanical because there are nearly 50 times as many establishments as district-occupation-generation triples in our sample.
Table 1.1: Summary Statistics: German Microdata

<table>
<thead>
<tr>
<th></th>
<th>1995</th>
<th>2014</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Number of observations</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Born before 1960 (“Old”)</td>
<td>185,751</td>
<td>96,045</td>
</tr>
<tr>
<td>Born after 1960 (“Young”)</td>
<td>251,451</td>
<td>538,590</td>
</tr>
<tr>
<td><strong>Mean log wage</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Born before 1960 (“Old”)</td>
<td>4.54</td>
<td>4.42</td>
</tr>
<tr>
<td>Born after 1960 (“Young”)</td>
<td>4.15</td>
<td>4.54</td>
</tr>
<tr>
<td><strong>Mean age</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Born before 1960 (“Old”)</td>
<td>44.86</td>
<td>60.53</td>
</tr>
<tr>
<td>Born after 1960 (“Young”)</td>
<td>28.22</td>
<td>39.56</td>
</tr>
</tbody>
</table>

Note: Sample of male workers in LIAB data, living in West Germany, employed full-time with a positive wage in 120 occupations. Generations as defined in the table.
1.3 Impact of new technologies on cognitive-intense occupations in Germany

This section investigates the robustness of the results presented in Section 6.2 of the paper as well as present some additional results of interest.

Cognitive intensity and labor market outcomes across occupations. We first report the impact of cognitive-intensity on occupation employment growth for different time horizons. The estimates in Table 1.2 show that results are qualitatively similar for 1995-2000 and 1995-2010. We can also see that the estimated coefficients increase continuously throughout the period of analysis.

We then investigate the impact of cognitive-intensity on occupation employment growth with a more flexible specification that allows for different coefficients for different levels of cognitive-intensity. As is clear from Table 1.3, the results in Table 1 of the paper are driven largely by an increase in employment for all generations in the most cognitive intensive occupations (above the 60th percentile of cognitive intensity). This increase is substantially stronger for the young generation. Some evidence of polarization is also evident for the young generation, as they also disproportionately enter the least cognitive intensive occupations.

Table 1.4 investigates the robustness of the estimates of equation (23) reported in Table 1 of the paper. Panel A of Table 1.4 reports similar results when we include occupation-level controls for import and export exposure and the growth in the fraction of migrants in the occupation. Panel B shows that results are also robust to restricting the sample to native-born German males only. Panel C presents results where the “Young” generation is defined alternatively as those born after 1965 or 1955. As expected, when the definition of the young generation is further restricted to include only more recent cohorts, the coefficient on “Young” is stronger. The opposite happens if we relax the young definition to include older cohorts. Panel C also shows that results are similar if the “Young” generation is defined as those aged below 40 in each year (as in Figure 4 of the paper).
Table 1.2: Cognitive intensity and labor market outcomes across occupations in Germany

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Employment Growth</th>
<th></th>
<th>Real Payroll Growth</th>
<th></th>
<th>Trainee Growth</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All Young Old</td>
<td>All Young Old</td>
<td></td>
<td>All Young Old</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1) (2) (3)</td>
<td>(4) (5) (6)</td>
<td>(7)</td>
<td>(8) (9) (10)</td>
<td>(11) (12)</td>
</tr>
<tr>
<td>Panel A: Change in 1995-2000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cognitive intensity</td>
<td>0.388*** (0.076)</td>
<td>0.650*** (0.098)</td>
<td>0.113*** (0.043)</td>
<td>0.340*** (0.048)</td>
<td>0.616*** (0.070)</td>
</tr>
<tr>
<td>Panel B: Change in 1995-2005</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cognitive intensity</td>
<td>0.778*** (0.111)</td>
<td>1.150*** (0.130)</td>
<td>0.290*** (0.079)</td>
<td>0.741*** (0.086)</td>
<td>1.158*** (0.114)</td>
</tr>
<tr>
<td>Panel C: Change in 1995-2010</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cognitive intensity</td>
<td>1.110*** (0.137)</td>
<td>1.523*** (0.149)</td>
<td>0.454*** (0.125)</td>
<td>1.036*** (0.111)</td>
<td>1.525*** (0.133)</td>
</tr>
<tr>
<td>Panel D: Change in 1995-2014</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cognitive intensity</td>
<td>1.488*** (0.225)</td>
<td>1.894*** (0.234)</td>
<td>0.871*** (0.229)</td>
<td>1.535*** (0.227)</td>
<td>2.029*** (0.238)</td>
</tr>
</tbody>
</table>

Note. Sample of 120 occupations. Each panel reports the estimate for the dependent variable over the indicated time period. Young cohort defined as all workers born after 1960 and Old cohort as all workers born before 1960. Robust standard errors in parentheses.

* p < 0.1, ** p < 0.05, *** p < 0.01

Table 1.3: Cognitive intensity and labor market outcomes across occupations in Germany: Percentiles specification

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Employment Growth</th>
<th></th>
<th>Real Payroll Growth</th>
<th></th>
<th>Trainee Growth</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All Young Old</td>
<td>All Young Old</td>
<td></td>
<td>All Young Old</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1) (2) (3)</td>
<td>(4) (5) (6)</td>
<td>(7)</td>
<td>(8) (9) (10)</td>
<td>(11) (12)</td>
</tr>
<tr>
<td>Low: below P30</td>
<td>-0.012 (0.128)</td>
<td>0.286** (0.137)</td>
<td>-0.946*** (0.129)</td>
<td>0.220* (0.132)</td>
<td>0.590*** (0.140)</td>
</tr>
<tr>
<td>Medium: P30-P60</td>
<td>-0.054 (0.194)</td>
<td>-0.046 (0.205)</td>
<td>0.031 (0.208)</td>
<td>-0.086 (0.195)</td>
<td>-0.036 (0.208)</td>
</tr>
<tr>
<td>High: above P60</td>
<td>0.812*** (0.156)</td>
<td>1.038*** (0.166)</td>
<td>0.531*** (0.016)</td>
<td>0.816*** (0.158)</td>
<td>1.099*** (0.169)</td>
</tr>
</tbody>
</table>

Note. Sample of 120 occupations. The table reports the estimate for the dependent variable over the time period 1995-2014. Occupations have been classified into 100 percentiles based on cognitive intensity, and separate coefficients estimated for percentiles below 30, 30-60 and above 60. Young generation defined as all workers born after 1960 and Old generation as all workers born before 1960. Robust standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01
Table 1.4: Cognitive intensity and labor market outcomes across occupations in Germany: Robustness

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Employment Growth</th>
<th>Trainee Growth</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All (1)</td>
<td>Young (2)</td>
</tr>
</tbody>
</table>

**Panel A: Alternative control set, 1995-2014**

- Controls for immigration and trade
  - 1.426*** (0.261)
  - 1.807*** (0.279)
  - 0.841*** (0.252)
  - 0.966*** (0.376)
  - 2.029*** (0.457)

**Panel B: Alternative sample definition, 1995-2014**

- Native-born Males Only
  - 1.396*** (0.226)
  - 1.807*** (0.235)
  - 0.778*** (0.231)
  - 1.029*** (0.340)
  - 2.194*** (0.385)

**Panel C: Alternative generation definition, 1995-2014**

- Young: Born after 1965
  - 1.488*** (0.225)
  - 2.137*** (0.299)
  - 0.857*** (0.246)
  - 1.280*** (0.387)
  - 2.121*** (0.385)

- Young: Born after 1955
  - 1.488*** (0.225)
  - 1.639*** (0.268)
  - 0.967*** (0.290)
  - 0.671* (0.395)
  - 2.121*** (0.385)

- Young: Aged Below 40 in each year
  - 1.488*** (0.225)
  - 1.748*** (0.294)
  - 0.773*** (0.246)
  - 0.975** (0.383)
  - 2.121*** (0.385)

*Note.* Sample of 120 occupations, sample periods as defined in the table. Columns (1)–(3) report the estimated coefficient on the occupation’s cognitive intensity in equation (23) of the paper. Column (4) reports the difference between the coefficients in columns (3) and (2). Each row defines a separate robustness exercise. The row "Controls for immigration and trade" includes a set of baseline controls: growth in occupational exposure to exports during the sample period, growth in occupational exposure to imports during the sample period, and growth in the fraction of immigrants in the occupation during the sample period. Robust standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01
Dynamic adjustment to broadband internet adoption across regions and occupations. We first turn to a more careful investigation of the robustness of the results in Figure 5 in the paper. Table 1.5 investigates how our baseline set of controls affects estimates. The three panels of Table 1.5 present estimates for the entire post-shock period of the sample (1999-2014, Panel A), the period during which DSL was rolled out across German regions (1999-2007, Panel B), and the period before the shock (1996-1999, Panel C). Each panel includes the results of our baseline specification, as well as alternative specifications in which (i) we drop the pre-trend control, and (ii) we augment baseline controls with district-generation-year fixed effects.

Consider first the impact of the pretrend control in the second row of each panel. Results indicate that this control increases the magnitude and the precision of the estimates coefficients in the period of 1999-2007 and 1999-2014. However, it has the opposite impact on the pre-shock period of 1996-1999. In this pre-shock period, there are marginally significant negative responses without the pretrend control.

Turning to the specification including district-generation-year fixed effects, we can see that results are remarkably similar to our baseline estimates. This is reassuring as this specification includes a restrictive set of controls that absorb all potential confounding shocks that affect each district-generation pair in a year. In this case, identification comes purely from the differential effect of early broadband expansion on occupations with a higher cognitive intensity. That is, this control set captures any pre-existing variation that might have resulted in a district receiving broadband access early, including differential immigration into a district that received DSL or differential aging or birth patterns in the district over time.

Table 1.6 investigates the robustness of the baseline estimates in Figure 5 of the paper to the sample specification. The two panels present estimates for the entire post-shock period of the sample (1999-2014, Panel A), and the period during which DSL was rolled out across German regions (1999-2007, Panel B). All specifications include the baseline set of controls.

The second row of each panel shows that results are similar if we restrict the sample to only include workers born in Germany. This suggests that the inclusion of immigrants in our sample does not drive our baseline results.

We consider next several alternative definitions of the young generation based on (i) cohorts groups born after 1955, 1965 or 1970, and (ii) age groups aged
Table 1.5: Impact of early DSL adoption on more cognitive-intensive occupations: Alternative control sets

<table>
<thead>
<tr>
<th>Control Set</th>
<th>Employment Growth</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All</td>
</tr>
<tr>
<td><strong>Panel A: 1999-2014</strong></td>
<td></td>
</tr>
<tr>
<td>Baseline</td>
<td>0.240***</td>
</tr>
<tr>
<td>(0.085)</td>
<td>(0.154)</td>
</tr>
<tr>
<td>No Pretrend Control</td>
<td>0.177**</td>
</tr>
<tr>
<td>(0.087)</td>
<td>(0.114)</td>
</tr>
<tr>
<td>District-Year Effects</td>
<td>0.149**</td>
</tr>
<tr>
<td>(0.067)</td>
<td>(0.160)</td>
</tr>
<tr>
<td><strong>Panel B: 1999-2007</strong></td>
<td></td>
</tr>
<tr>
<td>Baseline</td>
<td>0.077*</td>
</tr>
<tr>
<td>(0.043)</td>
<td>(0.092)</td>
</tr>
<tr>
<td>No Pretrend Control</td>
<td>0.015</td>
</tr>
<tr>
<td>(0.061)</td>
<td>(0.085)</td>
</tr>
<tr>
<td>District-Year Effects</td>
<td>0.093</td>
</tr>
<tr>
<td>(0.060)</td>
<td>(0.098)</td>
</tr>
<tr>
<td><strong>Panel C: 1996-1999</strong></td>
<td></td>
</tr>
<tr>
<td>Baseline</td>
<td>-0.002</td>
</tr>
<tr>
<td>(0.026)</td>
<td>(0.030)</td>
</tr>
<tr>
<td>No Pretrend Control</td>
<td>-0.109*</td>
</tr>
<tr>
<td>(0.065)</td>
<td>(0.077)</td>
</tr>
<tr>
<td>District-Year Effects</td>
<td>0.012</td>
</tr>
<tr>
<td>(0.032)</td>
<td>(0.032)</td>
</tr>
</tbody>
</table>

**Note:** Sample of 2 cohorts, 120 occupations and 323 districts. Sample periods as defined in the table. Column (1) reports the estimated coefficient on interaction between the occupation cognitive intensity and district DSL access in equation (24) for a single generation of working-age employed individuals. Columns (2)-(3) report the estimated coefficients on interaction between the occupation cognitive intensity, generation dummies and district DSL access in equation (24) for the old and young generations. Column (4) reports the difference between the coefficients in columns (3) and (2). Generations are the baseline generations with young workers those born after 1960. All regressions are weighted by the district population size in 1999 and include a set of baseline district-level controls as well as occupation-year and generation-year fixed effects. Each row defines a separate robustness exercise. “District-Year Effects” are estimated as district-year fixed effects in column (1) and as district-year-generation fixed effects in columns (2)-(4). Standard errors clustered at the district-level in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01
young generation based on a lower or higher age cutoff in each year. This is consistent with our theory since the entering cohorts are those adjusting their skills in response to the introduction of broadband internet in the regional labor market.

The last row of each panel reports estimates when we restrict the sample by excluding workers employed in establishments belonging to the top 25 percentile of establishment sizes. This exercise accounts for the likelihood that the largest establishments in Germany acquired DSL earlier through specialized private connections. In this case, we would expect adjustment in these establishments to have occurred earlier, biasing our results to zero. In line with this intuition, estimated coefficients are stronger than the baseline for all workers in column (1) and for the young-old gap in column (4). This indicates that our instrument seems to generate variation in the roll-out of broadband internet that mostly affected the occupation composition of small establishments across German districts.
Table 1.6: Impact of early DSL adoption on more cognitive-intensive occupations: Sample selection

<table>
<thead>
<tr>
<th>Dependent variable: Employment Growth</th>
<th>All</th>
<th>Young</th>
<th>Old</th>
<th>Between</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample Definition</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td><strong>Panel A: 1999-2014</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Baseline</td>
<td>0.240***</td>
<td>0.482***</td>
<td>-0.065</td>
<td>0.546**</td>
</tr>
<tr>
<td>(0.085)</td>
<td>(0.154)</td>
<td>(0.193)</td>
<td>(0.287)</td>
<td></td>
</tr>
<tr>
<td>Native-born Males Only</td>
<td>0.223***</td>
<td>0.446***</td>
<td>0.074</td>
<td>0.372**</td>
</tr>
<tr>
<td>(0.078)</td>
<td>(0.143)</td>
<td>(0.144)</td>
<td>(0.208)</td>
<td></td>
</tr>
<tr>
<td>Young: born after 1970</td>
<td>0.714***</td>
<td>-0.048</td>
<td>0.789**</td>
<td></td>
</tr>
<tr>
<td>(0.182)</td>
<td>(0.242)</td>
<td>(0.371)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Young: born after 1965</td>
<td>0.612***</td>
<td>-0.171</td>
<td>0.783***</td>
<td></td>
</tr>
<tr>
<td>(0.157)</td>
<td>(0.201)</td>
<td>(0.303)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Young: born after 1955</td>
<td>0.573***</td>
<td>-0.298</td>
<td>0.871**</td>
<td></td>
</tr>
<tr>
<td>(0.196)</td>
<td>(0.233)</td>
<td>(0.355)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Young: Aged &lt; 35 in each year</td>
<td>0.612***</td>
<td>0.059</td>
<td>0.553***</td>
<td></td>
</tr>
<tr>
<td>(0.139)</td>
<td>(0.233)</td>
<td>(0.203)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Young: Aged &lt; 40 in each year</td>
<td>0.529***</td>
<td>0.076</td>
<td>0.453**</td>
<td></td>
</tr>
<tr>
<td>(0.164)</td>
<td>(0.163)</td>
<td>(0.237)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Young: Aged &lt; 45 in each year</td>
<td>0.445***</td>
<td>0.159</td>
<td>0.286</td>
<td></td>
</tr>
<tr>
<td>(0.170)</td>
<td>(0.198)</td>
<td>(0.266)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Small Establishments Only</td>
<td>0.309***</td>
<td>0.466***</td>
<td>-0.128</td>
<td>0.594**</td>
</tr>
<tr>
<td>(0.083)</td>
<td>(0.140)</td>
<td>(0.183)</td>
<td>(0.286)</td>
<td></td>
</tr>
<tr>
<td><strong>Panel B: 1999-2007</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Baseline</td>
<td>0.077*</td>
<td>0.223***</td>
<td>-0.138</td>
<td>0.361**</td>
</tr>
<tr>
<td>(0.043)</td>
<td>(0.092)</td>
<td>(0.116)</td>
<td>(0.177)</td>
<td></td>
</tr>
<tr>
<td>Native-born Males Only</td>
<td>0.054</td>
<td>0.145*</td>
<td>0.037</td>
<td>0.108</td>
</tr>
<tr>
<td>(0.045)</td>
<td>(0.092)</td>
<td>(0.105)</td>
<td>(0.171)</td>
<td></td>
</tr>
<tr>
<td>Young: born after 1970</td>
<td>0.449***</td>
<td>-0.070</td>
<td>0.518*</td>
<td></td>
</tr>
<tr>
<td>(0.120)</td>
<td>(0.191)</td>
<td>(0.289)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Young: born after 1965</td>
<td>0.298***</td>
<td>-0.168</td>
<td>0.465**</td>
<td></td>
</tr>
<tr>
<td>(0.092)</td>
<td>(0.118)</td>
<td>(0.183)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Young: born after 1955</td>
<td>0.203**</td>
<td>-0.155</td>
<td>0.358***</td>
<td></td>
</tr>
<tr>
<td>(0.087)</td>
<td>(0.115)</td>
<td>(0.167)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Young: Aged &lt; 35 in each year</td>
<td>0.118**</td>
<td>0.095</td>
<td>0.022</td>
<td></td>
</tr>
<tr>
<td>(0.066)</td>
<td>(0.095)</td>
<td>(0.130)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Young: Aged &lt; 40 in each year</td>
<td>0.195**</td>
<td>0.030</td>
<td>0.165</td>
<td></td>
</tr>
<tr>
<td>(0.086)</td>
<td>(0.104)</td>
<td>(0.166)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Young: Aged &lt; 45 in each year</td>
<td>0.206**</td>
<td>0.091</td>
<td>0.115</td>
<td></td>
</tr>
<tr>
<td>(0.090)</td>
<td>(0.111)</td>
<td>(0.174)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Small Establishments Only</td>
<td>0.129*</td>
<td>0.263**</td>
<td>-0.170</td>
<td>0.434**</td>
</tr>
<tr>
<td>(0.070)</td>
<td>(0.103)</td>
<td>(0.120)</td>
<td>(0.181)</td>
<td></td>
</tr>
</tbody>
</table>

*Note. Sample of 2 cohorts, 120 occupations and 323 districts. Sample periods as defined in the table. Column (1) reports the estimated coefficient on interaction between the occupation cognitive intensity and district DSL access in equation (24) for a single generation of working-age employed individuals. Columns (2)-(3) report the estimated coefficients on interaction between the occupation cognitive intensity, generation dummies and district DSL access in equation (24) for the old and young generations. Column (4) reports the difference between the coefficients in columns (3) and (2). All regressions are weighted by the district population size in 1999 and include a set of baseline district-level controls, pretrend controls, occupation-year and generation-year fixed effects. Each row defines a separate sample selection exercise: (i) baseline sample restricted to only Germans ("Native-born"), (ii) different definitions of young workers based on year of birth or age cutoff in each year, and (iii) baseline sample restricted to workers employed in establishments below the 75th percentile of all establishment sizes ("Small Establishments Only"). Standard errors clustered at the district-level in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01
1.4 Additional Figures and Tables

Figure 1.4: Impact of early DSL adoption on payroll in more cognitive-intensive occupations: Old and Young generations

(a) Relative payroll response for each generation
(b) Between-generation response difference

Note. Estimation of equation (24) in the sample of 2 cohorts, 120 occupations and 323 districts. Dependent variable: log employment. The left panel reports $\beta^g_t$ for old and young generations, and the right panel reports $\beta^{\text{young}}_t - \beta^{\text{old}}_t$. All regressions are weighted by the district population size in 1999 and include occupation-time and cohort-time fixed-effects. Baseline controls include the following district variables in 1999: college graduate population share, manufacturing employment share, immigrant employment share, district age composition, and the dependent variable pretrend growth in 1995-1999. Bars are the associated 90% confidence interval implied by the standard error clustered at the district level.
Figure 1.5: Impact of early DSL adoption on more cognitive-intensive occupations: All generations

(a) Relative employment response for all generations

(b) Relative payroll response for all generations

Note. Estimation of equation (24) in the sample of 120 occupations and 323 districts for a single generation of working-age employed individuals. Dependent variable: log employment (left) and log payroll (right). All regressions are weighted by the district population size in 1999 and include occupation-time fixed-effects. Baseline controls include the following district variables in 1999: college graduate population share, manufacturing employment share, immigrant employment share, district age composition, and the dependent variable pre-shock growth in 1995-1999. For each year, the dot is the point estimate of $\beta^F_{all}$, and the bar is the associated 90% confidence interval implied by the standard error clustered at the district level.
Table 1.7: Impact of early DSL adoption on the number of trainees in more cognitive-intensive occupations

<table>
<thead>
<tr>
<th>Dependent variable: Training Growth</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td>(1)</td>
</tr>
<tr>
<td><strong>Panel A: 1999-2014</strong></td>
</tr>
<tr>
<td>Baseline</td>
</tr>
<tr>
<td>0.415*</td>
</tr>
<tr>
<td>(0.237)</td>
</tr>
<tr>
<td><strong>Panel B: 1999-2007</strong></td>
</tr>
<tr>
<td>Baseline</td>
</tr>
<tr>
<td>0.305</td>
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<tr>
<td>(0.247)</td>
</tr>
<tr>
<td><strong>Panel C: 1996-1999</strong></td>
</tr>
<tr>
<td>Baseline</td>
</tr>
<tr>
<td>-0.093</td>
</tr>
<tr>
<td>(0.044)</td>
</tr>
</tbody>
</table>

Note. Sample of 120 occupations and 323 districts. Sample periods as defined in the table. Table reports the estimated coefficient on interaction between the occupation cognitive intensity and district DSL access in equation (24) for a single generation of working-age individuals whose employment status is a trainee or intern in each year. All regressions are weighted by the district population size in 1999 and include a set of baseline district-level controls as well as occupation-year fixed effects. Standard errors clustered at the district-level in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01
2 Numerical Analysis

This appendix discusses in detail the parameterization of the model. We first present the theoretical impulse response functions for the relative employment of different worker generations. Second, we describe the procedure to select the parameters that match the theoretical and empirical impulse response functions. Finally, we use the parametrized model to quantitatively evaluate the dynamic adjustment to cognitive-biased technological innovations.

2.1 Impulse response functions of relative employment by generation

As a first step to parametrize our theory using the empirical impulse response functions in Section 6.2 of the paper, we derive the theoretical responses of generation-specific relative employment. To this end, we consider the same one-time permanent change in $A$ at $t = 0$. We define older generations as those born before period $t = -x$ and younger generations as those born at period $t = -x$. In period $t \geq 0$, the relative high-tech employment of these worker generations are given by

$$e_{\text{old}}^i_t = \frac{\int_{l_i}^{1} s_0(i)di}{\int_{0}^{l_i} s_0(i)di} \quad \text{and} \quad e_{\text{young}}^i_t = \tilde{x}_0 e^{-\delta t} \int_{l_i}^{0} s_0(i)di + \delta \int_{0}^{t} e^{\delta(\tau-t)} \int_{l_i}^{1} \tilde{s}_\tau(i)di d\tau \int_{0}^{1} \tilde{s}_\tau(i)di d\tau,$$

where $\tilde{x}_0 \equiv 1 - e^{-\delta x}$ is the population share of the young generation at $t = 0$.

For both worker groups, the technology-skill assignment is identical and determined by the threshold $l_i$. Notice that all workers of the old generations have the pre-shock skill distribution, $s_0(i)$. However, the skill distribution of young generations combines the pre-shock distribution, $s_0(i)$, and the post-shock lotteries, $\tilde{s}_\tau(i)$. The overlapping generation structure of the model implies that the relative share of workers in the young generation with the pre-shock skill distribution decays at the constant rate $\delta$.

We allow the young group to include workers born before the shock (since $x \geq 0$). This circumvents the challenge of identifying the cohorts that start adjusting their skills after the shock, which arises because, in practice, technologies may not be adopted instantaneously and young workers may still invest on skills after entering the labor force (in the form of vocational training or on-the-job learning).
It is also possible to allow part of the workers born before the shock to adjust their skills at \( t = 0 \). In this case, rather than \( s_0(i) \), the initial skill distribution would be a mix of \( s_0(i) \) and \( \tilde{s}_0(i) \). This extension does not alter our main qualitative insights, but reduces the magnitude of the short-to-long adjustment in the economy.

**Relative employment of old generation.** We show below that the change in the relative employment of old generations is

\[
\Delta \log e_{t}^{\text{old}} \approx \frac{\eta}{\theta + \kappa \eta} \frac{1}{e_H} \left( 1 - \frac{\psi}{\chi} \left( 1 - e^{-\lambda t} \right) \right) (\theta - 1) \Delta \log A,
\]

(1)

where \( e_H \) is the high-tech employment share at \( t = 0^- \).

Among old generations, the increase in the relative productivity of high-tech production induces the reallocation of workers towards high-tech production whenever \( \theta > 1 \). The expression indicates that this positive effect on relative high-tech employment becomes weaker over time. This follows from the expansion of high-\( i \) skills among younger generations, which displaces old workers with marginal skills from high-tech production – i.e., those with skills \( i \in (l_0, l_\infty) \).

Importantly, expression (1) shows that the magnitude of the increase in relative employment of older generations is decreasing in the degree of technology-skill specificity (i.e., increasing in \( \eta \)).

**Relative employment of young generation.** Turning to the employment response among young generations, we show below that

\[
\Delta \log e_{t}^{\text{young}} \approx \Delta \log e_{t}^{\text{old}} + \frac{\psi}{\chi} \frac{1 - e^{-\lambda t}}{1 - (1 - \tilde{x}_0) e^{-\delta t}} (\theta - 1) \Delta \log A.
\]

(2)

This expression indicates that the evolution of the allocation of young workers has two components. The first term captures the change in technology-skill assignment and, since it is the only determinant of the relative employment of old generations, it can be approximated by \( \Delta \log e_{t}^{\text{old}} \). The second term captures the change in the skill investment decision of incoming cohorts. At each point in time, this term is positive as young workers distort skill investment towards high-\( i \) skills that became more valuable in high-tech production. We can also show that the between-generation difference grows shortly after the shock. Importantly, expression (1) indicates that the between-generation difference in the response of relative employment is decreasing in the skill investment cost (i.e., it is increasing...
2.1.1 Proof of equations (1)–(2)

Proof of equation (1). We first use a first-order approximation to write the log-change in relative high-tech employment in terms of changes in the high-tech employment share:

\[
\Delta \log \left( e_{t}^{old} \right) = \log \left( \frac{e_{t}^{old}}{e_{0}^{old}} \right) \approx \frac{1}{(1 - e_{H,\infty})e_{H,\infty}} \left( e_{H,t}^{old} - e_{H,0}^{old} \right)
\]

where \( e_{H,t}^{old} = \int_{l_{t}}^{1} s_{0}(i)di \).

Since \( \Delta \left( \frac{1}{(1-e_{H,\infty})e_{H,\infty}} \right) \left( e_{H,t}^{old} - e_{H,0}^{old} \right) \) is a second order term, we get the approximation:

\[
\Delta \log \left( e_{t}^{old} \right) \approx \frac{1}{(1 - e_{H,0}^{-})e_{H,0}^{-}} \left( e_{H,t}^{old} - e_{H,0}^{old} \right)
\]

We have that

\[
e_{H,t}^{old} - e_{H,0}^{old} = \int_{l_{t}}^{1} s_{0}(i)di - \int_{l_{0}^{-}}^{1} s_{0}(i)di
\]

By approximating these expressions around \( l \),

\[
e_{H,t}^{old} - e_{H,0}^{old} \approx -s_{0}(l)l \left( \Delta \log(l_{\infty}) + \hat{\Delta} \right)
\]

\[
\approx (s_{0}(l)l) \eta \Delta \log(\omega_{t})
\]

\[
\approx (s_{0}(l_{0}^{-})l_{0}^{-}) \eta \Delta \log(\omega_{t})
\]

\[
\approx (1 - e_{H,0}^{-}) \eta \Delta \log(\omega_{t})
\]

where the third equality follows from the fact that \( \Delta (s_{0}(l)l) \Delta \log(\omega_{t}) \) is a second order term, and the last equality follows from normalizing the initial skill distribution to be uniform (which implies \( s_{0}(l_{0}^{-})l_{0}^{-} = 1 - e_{H,0}^{-} \)).

Combining the two expressions,

\[
\Delta \log \left( e_{t}^{old} \right) \approx \frac{1}{e_{H,0}^{-}} \eta \Delta \log(\omega_{t})
\]
Using the demand expression in equation (2) of the paper,
\[ \Delta \log \left( e_t^{old} \right) \approx \frac{1}{e_{H,0^-}} \eta \left( -\frac{1}{\theta - 1} \log y_t + \Delta \log A \right) \]

Using the expression for the evolution of \( y_t \) in Proposition 1 of the paper,
\[ \Delta \log \left( e_t^{old} \right) \approx \frac{1}{e_{H,0^-}} \frac{\eta}{\theta + \kappa \eta} \left( -1 - \kappa \eta - \frac{\psi}{\chi} (\theta - 1)(1 - e^{-\lambda t}) + (\theta + \kappa \eta) \right) \Delta \log A \]
\[ \Delta \log \left( e_t^{old} \right) \approx \frac{1}{e_{H,0^-}} \frac{\eta}{\theta + \kappa \eta} \left( 1 - \frac{\psi}{\chi} (1 - e^{-\lambda t}) \right) (\theta - 1) \Delta \log A, \]
which is identical to (1).

**Proof of equation (2)**. We first use a first-order approximation to write the log-change in relative high-tech employment in terms of changes in the high-tech employment share:
\[
\log \left( \frac{e_{t}^{young}}{e_{0}^{young}} \right) - \log \left( \frac{e_{t}^{old}}{e_{0}^{old}} \right) \approx \frac{1}{1 - e_{H,\infty}} \left( \frac{e_{t}^{young} - e_{0}^{young}}{e_{H,\infty}} - \frac{e_{t}^{old} - e_{0}^{old}}{e_{H,\infty}} \right) \\
= \frac{1}{(1 - e_{H,\infty})e_{H,\infty}} \left( \frac{e_{t}^{young} - e_{t}^{old}}{e_{H,\infty}} - \frac{e_{0}^{young} - e_{0}^{old}}{e_{0}^{young}} \right) \\
= \frac{1}{(1 - e_{H,\infty})e_{H,\infty}} \left( e_{t}^{young} - e_{t}^{old} \right)
\]

where the last equality follows from the fact that before the shock old and young make identical choices, \( e_{0}^{young} = e_{0}^{old} \).

Using the definition of employment shares for each generation,
\[
e_{H,t}^{young} - e_{H,t}^{old} \approx \frac{1}{1 - (1 - x_0)e^{-\delta t}} \left( \bar{x}_0 e^{-\delta t} \int_{l_t}^{1} s_0(i) di + \delta \int_{0}^{t} e^{\delta(\tau-t)} \int_{l_t}^{1} \bar{s}_\tau(i) di d\tau \right) - \int_{l_t}^{1} s_0(i) di \\
\approx \frac{1}{1 - (1 - x_0)e^{-\delta t}} \left( \delta \int_{0}^{t} e^{\delta(\tau-t)} \int_{l_t}^{1} (\bar{s}_\tau(i) - s_0(i)) di d\tau \right)
\]

Thus,
\[
\log \left( \frac{e_{t}^{young}}{e_{0}^{young}} \right) - \log \left( \frac{e_{t}^{old}}{e_{0}^{old}} \right) \approx \frac{1}{(1 - e_{H,\infty})e_{H,\infty}} \frac{1}{1 - (1 - x_0)e^{-\delta t}} \left( \delta \int_{0}^{t} e^{\delta(\tau-t)} \int_{l_t}^{1} (\bar{s}_\tau(i) - s_0(i)) di d\tau \right)
\]

(3)
We now consider the following approximation:

\[
\int_{l_i}^{1} (\tilde{s}_\tau(i) - s_0(i)) di \approx \int_{l}^{1} s(i)(\tilde{s}_\tau(i) - \tilde{s}_0(i)) di
\]

Then, we derive \( \hat{s}_0(i) \) using the expression for the stationary skill distribution

\[
s_0(i) = \frac{\tilde{s}(i)\alpha(i) \frac{\psi}{\varphi} (\omega_0 - \sigma(i)) \frac{\varphi}{\varphi} \sigma_{l_i > 0}}{\int_{0}^{l} \tilde{s}(j)\alpha(j) \frac{\varphi}{\varphi} dj + \int_{l_i}^{1} \tilde{s}(j)\alpha(j) \frac{\varphi}{\varphi} (\omega_0 - \sigma(j)) \frac{\varphi}{\varphi} dj}
\]

\[
\Rightarrow \quad \hat{s}_0(i) \approx - \left( \mathbb{I}_{i > l} - \int_{l}^{1} s(j) dj \right) \frac{\psi}{\rho + \delta} \Delta \log(\omega)
\]

Using the third part of Theorem 1 of the paper,

\[
\int_{l_i}^{1} (\tilde{s}_\tau(i) - s_0(i)) di \approx e_{H, \infty} (1 - e_{H, \infty}) \left( \psi \hat{q}_\tau + \frac{\psi}{\rho + \delta} \Delta \log(\omega) \right)
\]

\[
= e_{H, \infty} (1 - e_{H, \infty}) \psi (\hat{q}_\tau + \Delta \log(q))
\]

We now apply this expression into (3):

\[
\log \left( \frac{e_0^{young}}{e_0^{old}} \right) - \log \left( \frac{e_0^{old}}{e_0^{old}} \right) \approx \frac{\psi}{1 - (1 - \tilde{x}_0)e^{-\delta t}} \left( \delta \int_{0}^{l} e^{\delta(t-t)} (\hat{q}_\tau + \Delta \log(q)) d\tau \right)
\]

\[
\approx \frac{\psi}{1 - (1 - \tilde{x}_0)e^{-\delta t}} \left( \delta \int_{0}^{l} e^{\delta(t-t)} \hat{q}_0 e^{-\lambda t} d\tau + (1 - e^{-\delta t})\Delta \log(q) \right)
\]

\[
\approx \frac{\psi}{1 - (1 - \tilde{x}_0)e^{-\delta t}} \left( \frac{\delta}{\lambda - \delta} (e^{-\delta t} - e^{-\lambda t})\hat{q}_0 + (1 - e^{-\delta t})\Delta \log(q) \right)
\]

Notice that Proposition 1 of the paper implies that

\[
\Delta \log(q) = \frac{1}{\chi} (\theta - 1) \Delta \log A
\]

\[
\Delta \log(q_0) = \frac{1}{\chi} \left( 1 + \frac{\lambda - \delta}{\delta} \right) (\theta - 1) \Delta \log A
\]

\[
\hat{q}_0 = \Delta \log(q_0) - \Delta \log(q) = \frac{1}{\chi} \frac{\lambda - \delta}{\delta} (\theta - 1) \Delta \log A
\]
Thus,
\[
\log\left(\frac{e_{\text{young}}^{0-}}{e_{\text{old}}^{0-}}\right) - \log\left(\frac{e_{\text{old}}^{0-}}{e_{\text{old}}^{0-}}\right) \approx \frac{\psi}{\chi} \frac{1}{1 - (1 - \tilde{x}_0)e^{-\delta t}} \left( (e^{-\delta t} - e^{-\lambda t}) + (1 - e^{-\delta t}) \right) (\theta - 1) \log A
\]
\[
\approx \frac{\psi}{\chi} \frac{1 - e^{-\lambda t}}{1 - (1 - \tilde{x}_0)e^{-\delta t}(\theta - 1)\Delta \log A}
\]
which is equivalent to (2).

2.2 Parameterization by impulse response matching

We now describe how to parametrize our theory to match the empirical impulse response functions in Section 6.2. To this end, we map the \( H \) technology in our theory to the set of production activities performed by cognitive-intensive occupations. We calibrate our theory in two steps. In the first step, we exogenously specify a subset of parameters and functions in the theory. We set the discount rate to match an annual interest rate of 2%, \( \rho = 0.02 \). We calibrate the elasticity of substitution across cognitive and non-cognitive intensive occupations to \( \theta = 3 \). Finally, for all welfare calculations, we specify welfare-weights \( r_{e-rt} \) with \( r = \rho + \delta \) so that the social discounting of future generations is identical to the discounting of worker’s future utility.

We also specify functional forms for the productivity of skill types in the two technologies. We abstract from differences in non-cognitive productivity across skills by normalizing \( \alpha(i) \equiv 1 \). This implies that, for any given worker generation, employment and payroll responses are both driven by the degree of technology-skill specificity in the economy.\(^2\) In addition, we assume that \( \sigma(i) \) takes the form of a logistic function:
\[
\sigma(i) = \frac{e^{\sigma(i-l)}}{1 + e^{\sigma(i-l)}}
\]
where \( l \) is the assignment threshold in the initial stationary equilibrium. This specification is a tractable manner of capturing technology-skill specificity in the economy. It implies that the equilibrium exists for any \( \sigma > 0 \) since the relative productivity is bounded. Also, by setting the midpoint of the function to \( l \), the parameter \( \sigma \) controls the elasticity of \( \sigma(i) \) for the marginal skill types in the initial equilibrium (i.e., \( i \) close to \( l \)). Thus, \( \sigma \) specifies the magnitude of technology-skill productivity.

\(^2\)The function form of \( \alpha(i) \) controls how labor earnings respond to changes in the employment composition across technologies – for a discussion, see Adão (2016). Alternative specifications of \( \alpha(i) \) can thus be used to match responses in relative earnings for different worker generations.
specificity, $1/\eta$.

In the second step, we use the estimated responses of Section 6.2 to calibrate $(\delta, \sigma, \psi)$. In doing so, we select the distribution of innate ability to normalize the initial skill distribution to be uniform: $s_0(i) \equiv 1$.\footnote{In this calibration, we select the distribution of innate ability distribution, $s(i)$, to generate a uniform distribution of skills in the initial equilibrium: $s_0(i) \equiv 1$. In our theory, this normalization is innocuous since it does not affect changes in the skill distribution for a given change in $q$ conditional on setting $\eta$ to match the short-run employment change.} We formally present the parametrization procedure next, along with an analysis of the model fit. For all parameters, we assume that the shock starts with the roll-out of broadband internet in 2003. We then select parameters to match the estimates for the period of 2008 to 2014 in which we find statistically significant response in the relative payroll and relative employment of cognitive-intensive occupations.

**Generation size: $\delta$ and $\bar{x}_0$.** We first set $\bar{x}_0$ to match the 60% share of young workers in the national population in 1997. We then select $\delta$ to match the incline of 25 p.p. in the share of young workers in population between 1997 and 2014. Specifically, we select $x$ and $\delta$ such that

$$\hat{\delta} = \frac{1}{2014 - 1997} \log(0.40/0.15)$$

$$x = -\frac{1}{\delta} \log 0.4.$$

We obtain $\delta = 0.0574$. This says that the expected work life of a worker after turning 40 years is 18 further years.

**Rate of convergence: $\lambda$.** Proposition 1 in the paper implies that it is possible to write the impulse response function of relative output as

$$\Delta \log(y_t) = \alpha_0 + \alpha_1 e^{-\lambda t}$$

where $\alpha_0 > 0$, $\alpha_1 < 0$, and $\lambda > 0$.

We select the parameter $\lambda$ to match the growth in the estimates response of relative payroll of more cognitive-intensive occupations:

$$\hat{\lambda} = \text{arg min} \sum_{t=2008}^{2014} \left[ (\hat{\beta}_t^y - \hat{\beta}_{2007}^y) - \alpha_1 e^{-\lambda(t-2007)} \right]^2$$

\footnote{In this calibration, we select the distribution of innate ability distribution, $s(i)$, to generate a uniform distribution of skills in the initial equilibrium: $s_0(i) \equiv 1$. In our theory, this normalization is innocuous since it does not affect changes in the skill distribution for a given change in $q$ conditional on setting $\eta$ to match the short-run employment change.}
where \( \hat{\beta}_y \) are the estimated coefficient reported in Panel B of Figure 5 of the paper.

The minimization problem in (4) yields \( \hat{\lambda} = 0.135 \). Figure 1 shows the fit of the calibrated model

**Cost of skill investment:** \( \psi \). Theorem 1 of the paper implies that

\[
\kappa \eta = \psi \hat{\lambda} - \theta \tag{5}
\]

where

\[
\alpha = \delta \left[ \left( \frac{\rho}{2} + \hat{\lambda} \right)^2 - \left( \frac{\rho}{2} \right)^2 - \delta (\rho + \delta) \right]^{-1} \tag{6}
\]

Using expression (2), we have that

\[
\Delta \log e_{\text{young}}^t - \Delta \log e_{\text{old}}^t = \frac{\psi}{\chi} \frac{1 - e^{-\hat{\lambda} t}}{1 - (1 - \tilde{x}_0) e^{-\delta t}} (\theta - 1) \Delta \log A. \tag{7}
\]

From Proposition 1 of the paper,

\[
(\theta - 1) \Delta \log (A) = \Delta \log (y_t) \left( \frac{1 + \kappa \eta}{\theta + \kappa \eta} + \frac{\psi}{\chi} \frac{1 - \theta - 1}{\theta + \kappa \eta} (1 - e^{-\hat{\lambda} t}) \right)^{-1} \tag{7}
\]

where \( \chi = (\theta + \kappa \eta) (\rho + \delta) + \psi \).

Combining these two expressions, we get that

\[
\frac{\Delta \log e_{\text{young}}^t - \Delta \log e_{\text{old}}^t}{\Delta \log y_t} = \frac{1 - e^{-\hat{\lambda} t}}{1 - (1 - \tilde{x}_0) e^{-\delta t}} \left( \frac{1 + \kappa \eta}{\theta + \kappa \eta} + \frac{\psi}{\chi} \frac{1 - \theta - 1}{\theta + \kappa \eta} (1 - e^{-\hat{\lambda} t}) \right)^{-1}. \tag{8}
\]

Using the expression for \( \kappa \eta \) in (5),

\[
\frac{\Delta \log e_{\text{young}}^t - \Delta \log e_{\text{old}}^t}{\Delta \log y_t} = \frac{1 - e^{-\hat{\lambda} t}}{1 - (1 - \tilde{x}_0) e^{-\delta t}} \left( (\rho + \delta) \frac{1 + \psi \hat{\alpha} - \theta}{\psi} + 1 - \frac{\theta - 1}{\psi \hat{\alpha} e^{-\hat{\lambda} t}} \right)^{-1}. \tag{9}
\]

We then define the function:

\[
F^\psi(\psi, t) \equiv \frac{1 - e^{-\hat{\lambda} t}}{1 - (1 - \tilde{x}_0) e^{-\delta t}} \left( (\rho + \delta) \frac{1 + \psi \hat{\alpha} - \theta}{\psi} + 1 - \frac{\theta - 1}{\psi \hat{\alpha} e^{-\hat{\lambda} t}} \right)^{-1}. \tag{10}
\]

To calibrate \( \psi \), we first our calibrated values of \( (\lambda, \delta, \rho) \) to compute \( \alpha \) using (6). Our baseline calibration implies that \( \hat{\alpha} = 3.484 \). We then select the parameter \( \psi \) to match the ratio of the between-generation employment response and the payroll
response:
\[ \hat{\psi} = \arg\min\limits_{\psi} \sum_{t=2008}^{2014} \left[ \frac{\hat{\beta}_{\text{young}} - \hat{\beta}_{\text{old}}}{\hat{\beta}_{\text{old}}} - F^\psi(\psi, t) \right]^2 \]  

(11)

where \( \hat{\beta}_{\text{young}} \) are the estimated coefficients reported in Panel B of Figure 5 of the paper, and \( \hat{\beta}_{\text{young}} - \hat{\beta}_{\text{old}} \) is the between-generation employment response obtained with the estimated coefficients reported in Panel A of Figure 5 of the paper.

The minimization problem in (11) yields \( \hat{\psi} = 0.345 \). Figure 2 shows the fit of the calibrated model.

**Technology-skill specificity: \( \eta \).** The combination of (1) and (7) implies that

\[ \frac{\Delta \log e_{\text{old}}}{\Delta \log y_t} \approx \frac{\eta}{e_{H,0} - 1 + \eta} \frac{1 - \frac{\psi}{\hat{\lambda}}(1 - e^{-\hat{\lambda} t})}{\frac{(\theta - 1)(1 - e^{-\hat{\lambda} t})}{\alpha(\rho + \hat{\delta}) + 1}}. \]

Using the expression for \( \kappa \eta \) in (5),

\[ \frac{\Delta \log e_{\text{old}}}{\Delta \log y_t} \approx \frac{\eta}{e_{H,0} - 1 + \psi \alpha - \theta + \frac{(\theta - 1)(1 - e^{-\hat{\lambda} t})}{\alpha(\rho + \hat{\delta}) + 1}}. \]  

(12)

We then define

\[ F^\eta(\eta, t) \equiv \frac{\eta}{e_{H,0} - 1 + \hat{\psi} \hat{\alpha} - \theta + \frac{(\theta - 1)(1 - e^{-\hat{\lambda} t})}{\alpha(\rho + \hat{\delta}) + 1}}. \]  

(13)

where \( (\delta, \hat{\lambda}, \hat{\psi}) \) are the calibrated parameters above and \( e_{H,0} \) is the initial share of employment in cognitive-intensive occupations.

We select the parameter \( \eta \) to match the ratio of the employment response of old workers and the payroll response:

\[ \hat{\eta} = \arg\min\limits_{\eta} \sum_{t=2008}^{2014} \left[ \frac{\hat{\beta}_{\text{old}}}{\hat{\beta}_{\text{old}}} - F^\eta(\eta, t) \right]^2 \]  

(14)

\( \hat{\beta}_{\text{young}} \) are the estimated coefficients reported in Panel B of Figure 5 of the paper, and \( \hat{\beta}_{\text{old}} \) are the estimated coefficients reported in Panel A of Figure 5 of the paper.

The negative point estimates reported in Panel A of Figure 5 of the paper imply that the minimization problem in (14) yields \( \hat{\eta} < 0 \). Since the employment
response of old generations is small and nonsignificant, we assume that they are identical to zero, which yields $\hat{\eta} = 0$. Hence, we calibrate $\eta = 0.01$ and evaluate the model predictions under alternative specifications of this parameter.

![Figure 1. Calibration of $\lambda$](image)

*Note.* Blue dots represent the point estimates reported in Panel B of Figure 5 of the paper. Black solid curve represents the best fit line with $\lambda = 0.135$ obtained from the solution of (4).
2.3 Dynamic responses to cognitive-biased technological innovations

We now present the dynamic responses in our parametrized model. As in Section 7 of the paper, we evaluate a shock to $A$ that leads to an increase in the employment share in cognitive-intensive occupations from 20% to 50%. Figure 3 presents the results.

Consider first the response at $t = 0$. Given that our theory abstracts from several additional sources of dynamics, it would be wrong to interpret the impact adjustment as happening instantaneously in reality. We view this short-run response as capturing changes over the time window encompassing dynamic forces triggered by other variables that are likely to move faster than the distribution of skills (e.g., physical capital). In other words, we prefer to interpret the “length” of the impact adjustment as related to the time that it takes for such faster moving variables to converge to the new long-run equilibrium. Results show that there is a substantial increase in the relative cognitive-intensive output in the short-run. This large response is a consequence of the large magnitude of the shock. This
becomes clear when we take into account that relative employment almost does
not change at impact because of the high technology-skill specificity (i.e., \( \eta \approx 0 \)). The combination of the large increase in relative output and the small increase in
relative employment translates into large changes in lifetime inequality.

Our results also indicate that the responses in all outcomes change substantially over time (measured in terms of worker generations, \( 1/\delta \approx 18\text{yrs} \)). Over the
course of the two generations following the shock, the responses in relative output doubles in magnitude due to the reallocation of workers across technologies.
Such a reallocation is entirely driven by incoming generations of young workers. This pattern is a consequence of the change in the skill distribution across generations. The bottom right panel shows that the initial spike in lifetime inequality induces young workers to invest in high-i skills allocated to cognitive-intensive occupations. This gives rise to substantial skill heterogeneity across generations.

As young generations replace old generations, the economy’s skill distribution becomes more biased towards high-i types, leading to a large decline in the present value of the relative wage in cognitive-intensive occupations (which recedes by more than 30% over the course of two generations).

3 Additional Results

3.1 Microfoundation of the Production Functions in equations (4)-(5) of the paper

Consider two firms: high-tech \((k = H)\) and low-tech \((k = L)\). Assume that the output of firm \(k\) at time \(t\) aggregates per-worker output \(x_{kt}(i)\),

\[
X_{kt} = \int_{0}^{1} x_{kt}(i)s_{kt}(i)di,
\]

where \(s_{kt}(i)\) is the quantity demanded of workers of type \(i\) at time \(t\) by firm \(k\).

The output of workers of type \(i\) depends on their skills to perform cognitive and noncognitive tasks, \(\{a_{C}(i), a_{NC}(i)\}\), as well as how intensely each task is used in the firm’s production process:

\[
x_{kt}(i) = a_{C}(i)^{\beta_{k}} a_{NC}(i)^{1-\beta_{k}},
\]

where \(\beta_{k}\) denotes the production intensity of firm \(k\) on cognitive tasks.
In our model, technology-skill specificity arises whenever firms are heterogeneous in terms of task intensity and workers are heterogeneous in terms of their task bundle. To see this, suppose that firm $H$’s technology uses cognitive tasks more intensely than firm $L$’s technology, $\beta_H > \beta_L$, and that a worker of type $i$ is able to produce a higher cognitive-noncognitive task ratio than a worker of type $j$, $a_C(i)/a_{NC}(i) > a_C(j)/a_{NC}(j)$. In this case, $i$ has a higher relative output with the cognitive-intensive technology $H$ than $j$, $x_{Ht}(i)/x_{Lt}(i) > x_{Ht}(j)/x_{Lt}(j)$, and, therefore, type $i$ is more complementary to the cognitive-intensive technology $H$ than type $j$.

To map this setting to the production functions in equations (4)-(5) of the paper, we assume that high-tech production is more intensive in cognitive tasks than low-tech production, $\beta_H > \beta_L$. We also assume that types differ in terms of their
skill bundle and, without loss of generality, impose that high-i types are relatively better in performing cognitive-intensive tasks.

1. High-tech technology $H$ uses cognitive tasks more intensely than Low-tech technology $L$: $\beta_H > \beta_L$.

2. Define $\sigma(i) \equiv \left( \frac{a_C(i)}{a_{NC}(i)} \right)^{\beta_H - \beta_L}$ and $\alpha(i) \equiv a_C(i)^{\beta_L} a_{NC}(i)^{1-\beta_L}$. Assume that high-i types have higher cognitive-noncognitive task ratio: $\sigma(i)$ is increasing in $i$.

References

