Online Appendix

Do Recessions Accelerate Routine-Biased Technological Change? Evidence from Vacancy Postings

Brad Hershbein
Upjohn Institute and IZA

Lisa B. Kahn
Yale University NBER and IZA

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A Data Appendix

It is estimated that as of 2014 between 60 and 70 percent of all job postings could be found online (Carnevale, Jayasundera, and Repnikov 2014). Indeed, The Conference Board discontinued its-long-running, print-based Help-Wanted Advertising Index in 2008, after having begun a Help-Wanted Online Index in 2005 (HWOL).[1] Several other private-sector firms also began to track online job postings in the 2000s by using web-crawling and data-scraping methods. In this study, we employ data from one such firm, Burning Glass Technologies. This appendix discusses the representativeness of the data and investigates whether representativeness has changed over the time period of analysis.

A.1 Industry-Occupation Composition in BG

The BG database covers only vacancies posted on the Internet, as opposed to JOLTS or state vacancy reports that directly survey a representative sample of employers. To the extent that vacancies from certain industries and occupations are less likely to be posted electronically, as might be the case for many less-skilled jobs, they will be underrepresented in the data.[2] It is also possible that the BG database is not representative even of online job postings, as comprehensiveness rests on the strength of the company's algorithms to code information in the ads and get rid of duplicates. Carnevale, Jayasundera, and Repnikov (2014) show that the occupation-industry composition of the BG data are similar to that of the Conference Board's HWOL. Moreover, the authors audited a sample of job postings in the BG database and compared them to the actual text of the postings, finding that the codings for occupation, education, experience were at least 80 percent accurate.[3]

Figure A1 plots the distribution of BG ads across major industry groups, sorted from largest to smallest (solid bars), as well as the distribution of job vacancies in JOLTS (diagonal-lined bars). As mentioned, the BG database is meant to capture only electronically posted job ads; the universes of the data sources are thus not identical, but JOLTS is the best comparison available.[4] Despite the sample differences, the industry distributions

[1] See https://www.conference-board.org/data/helpwantedonline.cfm.

[2] Rothwell (2014) compares the occupational distributions from an extract of BG to those from state vacancy surveys for select metropolitan areas for which data are available. He finds that computer, management, and business occupations are overrepresented relative to the state vacancy surveys, while health care support, transportation, maintenance, sales, and food service workers are underrepresented.

[3] Furthermore, since BG regularly revises and attempts to improve its algorithms (applying them retroactively on the complete historical database of postings), and our extract is more recent than the one studied by Carnevale, Jayasundera, and Repnikov, it seems reasonable that their accuracy figure would be a lower bound for our sample.

[4] Both data sets cover 2007 and 2010–2015. The BG distribution is from our primary estimation sample (notably excluding ads with missing firms), though we obtain similar results for the distribution across all ads. JOLTS data are based on a monthly, nationally representative sample of approximately 16,000 business establishments drawn from unemployment insurance records; they count as a vacancy or job opening any position (including temporary and seasonal ones) that could start within 30 days and that the employer is actively trying to fill through a variety of means, of which posting a job ad (electronic or otherwise) is only

match each other reasonably well. BG is overrepresented in health care and social assistance, as well as in finance and insurance and education. It is underrepresented in accommodation and food services, public administration/government, and construction. However, most differences are small in magnitude.

A great advantage of the BG data over the JOLTS is that they allow us to categorize jobs by occupation at a detailed level. We thus also compare the occupational distribution of BG job ads to both the stock and flow of employment in the United States. We should not expect online job ads to precisely match either comparison group since occupations differ in turnover rates that would necessitate new hires (flows), and since they also differ in the extent to which they use vacancy postings (rather than informal hiring channels) to fill a slot. However, these comparisons help build intuition for the BG data set.

Figure A2 plots the distribution of BG ads across major occupation groups, sorted from largest to smallest (blue bars).[5] We show the distribution of the stock of employment based on the Bureau of Labor Statistics' Occupational Employment Statistics (OES) data (light blue, horizontal lines). We also show the occupational distribution of new job starts (job flows) based on longitudinally linked Current Population Survey (CPS) data (dark blue, diagonal lines).[6]

Perhaps not unexpectedly, BG has a much larger representation of computer and mathematical occupations, more than four times the OES and CPS shares. BG is also overrepresented among management, healthcare practitioners, and business and financial operations, although to lesser degrees. On the other hand, BG data are underrepresented in many of the remaining occupations—for example, in transportation, food preparation and serving, production, and construction. The OES and CPS distributions agree more closely, although there are notable gaps among occupations known to have very high (or very low) rates of turnover.

A.2 Representativeness of BG Data over Time

As noted in the text, our primary concern is that the representativeness of the sample changes over time. This would be a threat to internal validity in our analysis. Figure A3 gives a general sense of whether the representativeness of BG has changed over our sample period. On the x-axis we plot the deviation of the BG occupation share in 2007 from that occupation's share of CPS new job starts in the same year. For example, computer and mathematical occupations are shown on the far right, at roughly 11 percentage points (ppts)

one.

[5]For clarity, we use 2-digit Standard Occupational Classification codes in the figure. The regression analyses use more granular codings.

[6]All data sets cover 2007 and 2010–2015. The BG distribution is from our primary estimation sample, though, again, the distribution is similar for the full sample of ads. We define a new hire in the CPS as an individual who, from month t to month $t+1$, transitioned from non-employment to employment, reported a new employer, or reported changing occupations.

overrepresentation in BG compared to CPS. Construction is on the far left, at roughly 7 ppts underrepresented. On the y-axis we plot the deviation of the BG occupation share from its CPS share for each of the later years in the data. The markers are color-coded by year. The darkest markers plot the (2007, 2010) representativeness pair for each occupation; the lightest markers plot the (2007, 2015) representativeness pair. We also plot the 45-degree line as a benchmark: if representativeness of the BG data, relative to the CPS, remained constant over time, all markers should line up on the 45-degree line.

The figure shows that changes in representativeness over this time period are very small (most of the markers are close to the 45 degree line). To the extent that changes did occur, there is a tendency for them to have been in the direction of closer representativeness to the CPS. Computer and mathematical occupations, management occupations, and architecture and engineering occupations appear to have become less overrepresented, while health care and business and finance look fairly unchanged; administrative support, food, transportation, and production occupations have become slightly less underrepresented. For most of these occupations, though, the differences are quite small.

A.3 Skills Measures in BG

One of the most unique features of the BG data is the availability of skills measures. We argue that these stated preferences are informative about labor demand. Figures A4a and A4b crosscheck the average education requirements in BG with average education levels of employed workers at the MSA- and occupation-level, respectively. Using American Community Survey (ACS) data for overlapping sampling years, we rank both MSAs and occupations (four-digit SOC codes) by their average education of employed workers and plot the relationships between average education requirements and average education for 20 evenly sized employment bins, using smoothed local linear regression. As can be seen, at the levels of both MSA and occupation, the probability that an ad posts any education requirement is increasing with the average years schooling of employed workers (top left), as is the years of school conditional on any requirement (top right). Furthermore, the probability that an ad has a high school requirement is positively correlated with the share of workers that have exactly a high school diploma (bottom left), and the probability that an ad has a college requirement is positively correlated with the share of workers with exactly a bachelor's degree (bottom right).

A.4 Harte-Hanks Sample

We are grateful to Nick Bloom for providing us with an extract of the Harte-Hanks (HH) database, based on Bloom, Draca, and Van Reenen (2016). To construct our merged BG-HH sample, we begin with 15,093 BG firms that post in the 2010–2015 period and can also be matched to at least one ad in 2007 (9 percent of firms and 62 percent of ads). In this sample, we match a total of 78 percent of BG 2010–2015 ads (58 percent of firms) to HH firms; we did not attempt to match observations that did not meet the pre-post criterion.[7] We apply a multi-step approach to match firms. First, we match based on exact name, after regularizing firm names in both BG and HH (removing "inc.," "LLC," and other common suffixes, as well as punctuation and spaces). This accounts for 89 percent of ultimately matched firms and 92 percent of ultimately matched ads. Most of the remaining share of ultimate matches (6 percent of firms, 4 percent of ads) are obtained by dropping one at a time common strings, such as "hotel," "group," or "insurance," that might be part of the firm name in one dataset but not the other. We also obtain a small number of matches by removing any "s" at the end of the last word, either singularizing or removing possessives, and by replacing "univ" with "university"; these steps combined account for 3.7 percent of eventual firm and 2.6 percent of eventual ads matched. Finally, we match based on the first 10 characters of the firm name in each dataset, cleaning spurious matches by hand. This accounts for the remaining 1 percent of total firm and 2 percent of total ad matches.

A.5 Compustat Sample

We obtain Compustat data via Wharton Research Data Services. To construct our merged BG-Compustat sample, we again begin with the same sample as above, 15,093 BG firms that post in the 2010–2015 period and can also be matched to at least one ad in 2007 (9 percent of firms and 62 percent of ads). In this sample, we match a total of 41 percent of BG ads (10 percent of firms) to Compustat firms; we did not attempt to match observations that did not meet the pre-post criterion.[8] We apply a multi-step approach to match firms. We first match based on exact name, after the same cleaning procedure described above (removing punctuation, spaces, and words that are sometimes abbreviated). This step accounts for 84 percent of ultimately matched firms and 80 percent of matched ads. We supplement these matches with the sample of firms matched by Deming and Kahn (2018), which uses only BG firms posting in 2014 (16 percent of firms and 20 percent of ads).

[7] The HH database sampled roughly 500,000 U.S. sites each year prior to 2010, and roughly three million from 2010 onward. Although detailed sampling information is not available, and the HH database does not contain sampling weights, total employment among the sampled sites ranges from 39–57 million prior to the Great Recession and 101–114 million from 2010 onward. This represents about 30–40 percent of total payroll employment prior to 2010, and about 70–85 percent from 2010 onward. Our restriction imposes that firms be sampled in both periods.

[8] For context, the size of employment in Compustat is roughly half that of total employment in the U.S. For example, in 2014, the sum of employment listed in companies in Compustat was 70,505,000 and total payroll employment averaged 139,042,000. The Compustat employment figure includes both domestic and foreign workers, with no way to distinguish between the two. However, the employment comparison provides a useful benchmark.

A.6 Autor-Acemoglu routineness measures

Acemoglu and Autor (AA; 2011) use O*Net job attributes to define six standardized measures capturing the task content of occupations: non-routine cognitive analytical, non-routine cognitive interpersonal, non-routine manual physical, non-routine manual interpersonal, routine manual, and routine cognitive. We focus on the last two. The routine-manual index is created by summing studentized versions of three attributes ("Controlling Machines and Processes [4.A.3.a.3]," "Spend Time Making Repetitive Motions [4.C.2.d.1.i]," and "Pace Determined by Speed of Equipment [4.C.3.d.3]") and re-studentizing the sum. The routine cognitive index is created by summing studentized versions of three attributes ("Importance of Being Exact or Accurate [4.C.3.b.4]," "Importance of Repeating Same Tasks [4.C.3.b.7]," and (reverse-scaled) "Structured v. Unstructured Work [4.C.3.b.8]") and re-studentizing the sum. See AA for additional details. We depart slightly from AA in not using employment weights when creating the indices at the 6-digit SOC level, as we are interested in the distribution of routineness across occupations, not workers. In practice, this difference does not matter much. We aggregate to the four-digit SOC occupation category by taking an OES-employment weighted average across nested 6-digit occupations.

A.7 Current Population Survey and Occupational Employment Statistics Samples

Figure 7 in the main text explores the differential impact of the Bartik shock for routine-manual and routine-cognitive occupations, using Current Population Survey (CPS) microdata to calculate layoffs and Occupational Employment Statistics (OES) data to calculate wages and employment.

We work with the basic monthly CPS and harmonize both MSA and occupation codes. To harmonize MSA codes, we begin with the 2013 Office of Management and Budget (OMB) CBSA delineations (which the CPS began using in May 2014) and work backward in time. The CBSA codes from May 2004 though April 2014 can be converted to the 2013 standard using Census delineation files; in most cases these are one-to-one code changes or absorptions of an MSA into a larger one, although some MSAs stop being identifiable in the CPS and others start being identifiable.[9] Prior to May 2004, the CPS used the older PMSA coding scheme. We apply a crosswalk initially developed by the Social Security administration and maintained by the NBER to convert PMSAs to 2013-vintage CBSAs.[10] The more significant nature of the PMSA to CBSA switch results in several MSAs that do not cleanly map; the crosswalk maps 267 of 317 PMSAs into CBSAs at the exact county-level definition, although not all of these CBSAs are identifiable in the CPS from 2005 onward. Using these procedures,

[9] See https://www.census.gov/geographies/reference-files/time-series/demo/metro-micro/delineation-files.html.

[10] See http://www.nber.org/data/cbsa-msa-fips-ssa-county-crosswalk.html.

we consistently identify 149 MSAs (out of 381 used in the BG sample) between 2000 and 2015 in the CPS.

To harmonize occupation codes, we begin with the 2010 SOC coding scheme and work backward. The CPS uses 2010 Census occupation codes starting January 2011; these are converted to 2010 SOC codes using a Census crosswalk.[11] From January 2003 through December 2010, the CPS uses 2000 Census occupation codes. These occupation codes are first converted to the 2000 SOC system using a crosswalk maintained by IPUMS at the University of Minnesota.[12] The 2000 SOC codes are then converted to the 2010 SOC system using a BLS crosswalk (see https://www.bls.gov/soc/soc_2000_to_2010_crosswalk.xls) for occupations that match one-to-one and were simply recoded or for occupations that were combined; for occupations that split at the 6-digit level, we apply a stochastic crosswalk based on empirical shares observed in the IPUMS versions of the 2009 ACS (which contains the 2000 SOC) and the 2010–2012 ACS (which contains the 2010 SOC).[13] Finally, the CPS uses 1990 occupation codes prior to January 2003. To convert CPS years 2000 through 2002, we use the NBER version of CPS extracts files released by BLS.[14] These files contain 2000 Census occupation codes for CPS years 2000 through 2002, allowing use of the above procedure.

To determine layoff status, we first drop observations living in a non-metropolitan area or without a valid occupation code (individuals who had not worked in the preceding five years), as we cannot match an MSA shock or occupational routineness measure to these out-of-universe observations. We assign the status of an involuntary separation to individuals who answer the reason for unemployment question (pruntype) either "job loser/on layoff" or "other job loser." Although this question is asked only of the currently unemployed, we include in the universe all members of the experienced labor force (those with a valid occupation code). Note that this is a "stock" variable; we do not restrict layoffs to individuals who had been employed the previous month.

We also use CPS microdata to calculate employment-to-population ratios (bottom panel of figure 1 in the main text) and quit rates by education group (used as controls in appendix B.2). Note that these variables will be noisier than the unemployment rates and employment series calculated by the BLS (and used in the top panel of figure 1 in the main text).[15] We calculate employment-population ratios according to the standard definition (the sample-weighted share of employed persons divided by the population). To measure

[11]See https://www.census.gov/people/io/files/2010_OccCodeswithCrosswalkfrom2002-2011nov04.xls.

[12]See https://usa.ipums.org/usa/volii/census_occtooccsoc.shtml.

[13]Occupations that split were randomly assigned to one of the splits based on the empirical distribution of the splits in 2010–2012. Since these splits almost never cross the 4-digit SOC level, which we use in all analyses, measurement error from this stochastic assignment is trivial.

[14]See http://www.nber.org/data/cps_extract.html.

[15]BLS does not use microdata directly to calculate unemployment rates or payroll employment for local areas. Rather, these estimates are derived from time-series errors-in-variables models, using as primary inputs unemployment insurance claims and state-level CPS and payroll employment survey estimates. See https://www.bls.gov/lau/gen4models.pdf. Hence, demographic breakdowns are unavailable.

quit rates, we longitudinally link observations and define a quit as an individual who was either (a) employed in months t and $t+1$ but reported having changing employers in month $t+1$ (using the variable puiodp1), or (b) employed in month t, unemployed in month $t+1$, and gave as the reason for unemployment being a "job leaver" (using the pruntype variable). The denominator is the (weighted) count of longitudinally matched individuals who were employed in month t.

We use OES data to calculate the wages and employment shares used in figure 7 of the main text.[16] To make data comparable across years (from 2000 to 2015), we must use crosswalks for both MSA and occupation codes.

Data from 2000 to 2011 use SOC 2000 codes, which we map to SOC 2010 codes using the same procedure as with the CPS data. OES also uses a small number of temporary occupation codes in 2010 and 2011, which we must drop.

MSAs from 2005 onward use the OMB 2013 delineation, but years 2000–2004 use the 1999 delineation. We map old MSA codes to the new ones using data from the IPUMS versions of the 2000 Census and 2005–2011 ACS samples, where both measures are available, and keeping the modal new MSA match (based on sample weights).[17]

To better understand how layoffs (CPS) and wages (OES) vary with our key right-hand-side variables, we provide within-occupation-MSA estimates of equation (1) in the main text. These are summarized in figure A5. The differential (rather than main) effects on these variables for routine-cognitive and routine-manual occupations (described in equation (4) of the main text) are plotted in the main text in figure 7.

We estimate that between 2007 and 2009, a hard-hit MSA experiences an additional 1.2 ppt increase in layoff probability (the share of the sample that reports being involuntarily unemployed), relative to a less hard-hit MSA. This is roughly two-thirds of the average involuntary separation rate observed across the sample period. Effects remain elevated in 2010, before dropping to zero by 2012. Wage effects, in contrast, move more slowly. Although issues of selection preclude us from making causal statements (Martins, Solon and Thomas 2012), we find that hard-hit MSAs experience a drop in wages about 0.5 percent to 1.5 percent greater than less hard-hit MSAs, with this differential the largest over 2012–2014. As with the other labor market measures in figures 1, 4, and 7 of the main text, estimates preceding the Great Recession are close to zero. Thus, layoffs and wages were evolving similarly across MSAs, regardless of the size of the shock they would receive.

A.8 Sample Restrictions and the Bartik Shock

Table A1 examines how the probability of meeting certain sample criteria varies with the MSA-employment shock over time. Because we use a first-difference specification (see equa-

[16] Annual data at the MSA-occupation level can be obtained from the BLS: https://www.bls.gov/oes/tables.htm.

[17] See https://usa.ipums.org/usa-action/variables/MET2013#comparability_section.

tion (1) in the main text), the most relevant threat to internal validity would be if the *change* in the probability of meeting our sample criteria (from the base period) varies systematically with the Bartik shock. We generally find that this is not the case.

Column 1 explores the probability of ads missing firm name, and thus being excluded from our main sample. On average, 39% of ads are missing firm name, likely because they are posted to a recruiter's website. However, we find that the change in this probability from 2007 does not vary meaningfully with the Bartik shock. Most coefficients in column 1 are small in magnitude, change sign, and are statistically insignificant. The one exception is in 2012, where the estimate implies that hard-hit MSAs are 6.6 ppts less likely to have ads without a firm name, relative to 2007, than less hard-hit MSAs. This relative decline is significant at the 1 percent level. As pointed out in section 4, however, 2012 appears to be an unusual year in the BG data, and we express caution in overinterpretting any finding from this one year.

Column 2 explores the probability of being excluded from the sample of firms used for figure 3 in the main text (showing that upskilling in the later period is driven by the same firms that upskilled initially), by firms not posting at least five ads each in 2007 and 2010. About one-third of weighted observations in our main sample do not satisfy this criterion. We again find that the change in the share of ads within an MSA is unrelated to this sample restriction except for the anomalous 2012 (and weakly—at the 10 percent level—in 2011).

Column 3 looks at a related criterion: the probability of exclusion from the sample used for figure 5 in the main text (the differential upskilling effects for firms that have invested heavily in capital). For this sample we need to observe a firm in 2007 and again at least once in any later year. Among weighted observations in the firm sample, 31 percent do not meet this criterion. However, as can be seen, the change in satisfying the restriction does not vary with the Bartik shock. Aside from the one in 2012, coefficient estimates are statistically insignificant and small in magnitude.

In columns 4 and 5, we investigate whether the share of ads that can be matched at the firm level to Harte Hanks and Compustat, respectively, varies over time and with the Bartik shock. As noted in the text, about 80 and 40 percent of ads can be matched to HH and Compustat, respectively, conditional on meeting the criteria in column 3. In the table, we estimate the change in the probability of not matching to these samples among all ads with a firm identifier, not conditional on the column 3 criterion; here, non-match rates are 50 percent for HH and 72 percent for Compustat. Relative to these rates, the estimates in columns 4 and 5 are small in magnitude; none is statistically insignificant, and signs vary.

Finally, Column 6 explores whether a site (akin to an establishment) is present in the database at least once in 2002, 2004, or 2006, among the entire sample of firms in HH (not just those matching to BG). This restriction is necessary to generate PCs normalized by pre-recession employment at the site level. We aggregate this probability to the MSA level, taking an employment-weighted average across sites. Overall, 35 percent of employment in

HH do not meet this restriction. In general, we find that the change in this probability from 2006 does not vary with the Bartik shock. Point estimates are small and statistically insignificant, with one marginal exception in 2000.

Figure A1: Industry Distributions: BG, JOLTS: 2007, 2010-2015

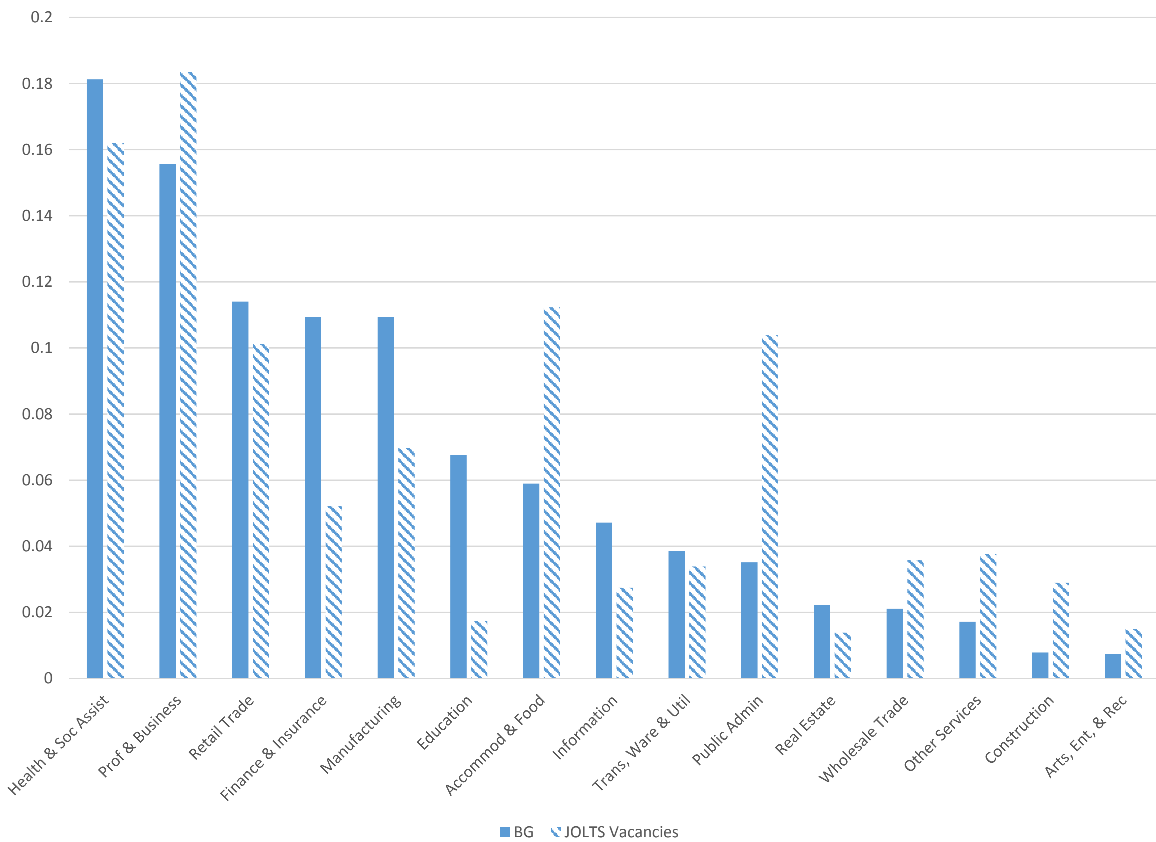


Figure A2: Occupation Distributions: BG, New Jobs (CPS) and Employment (OES)

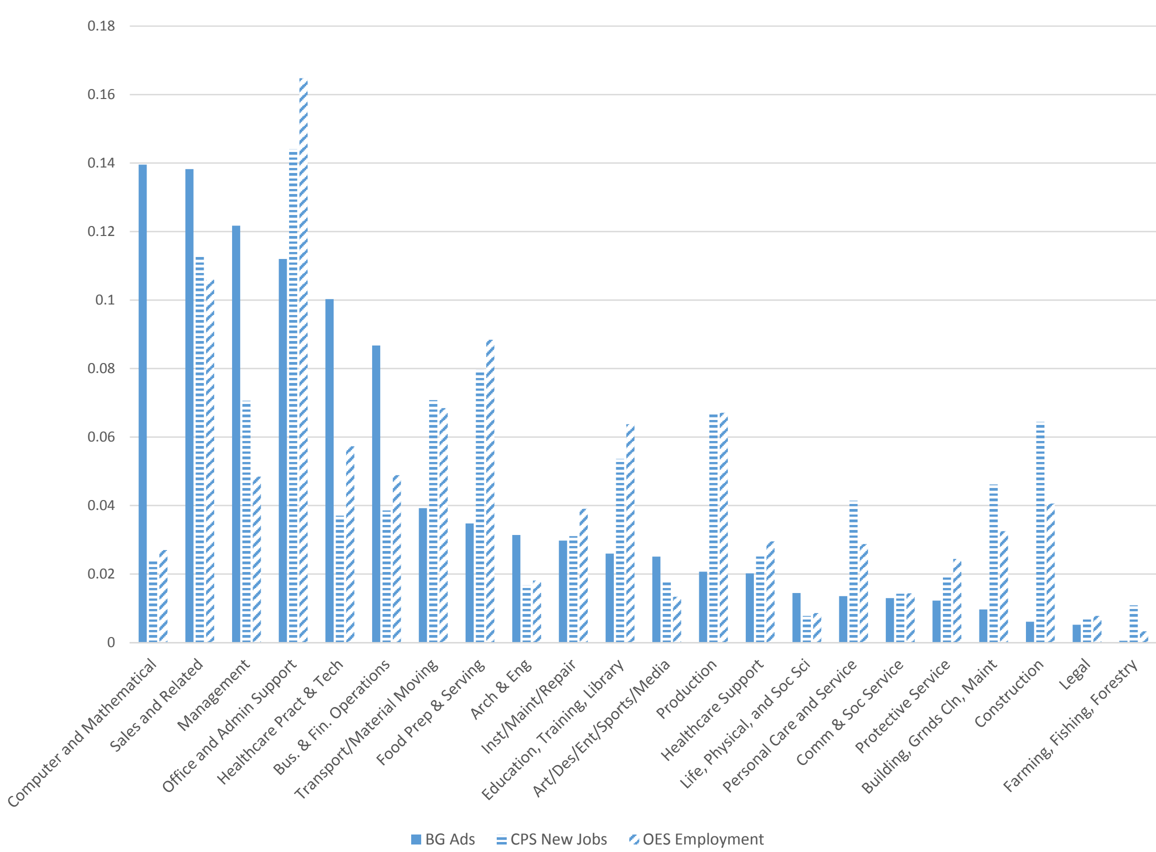
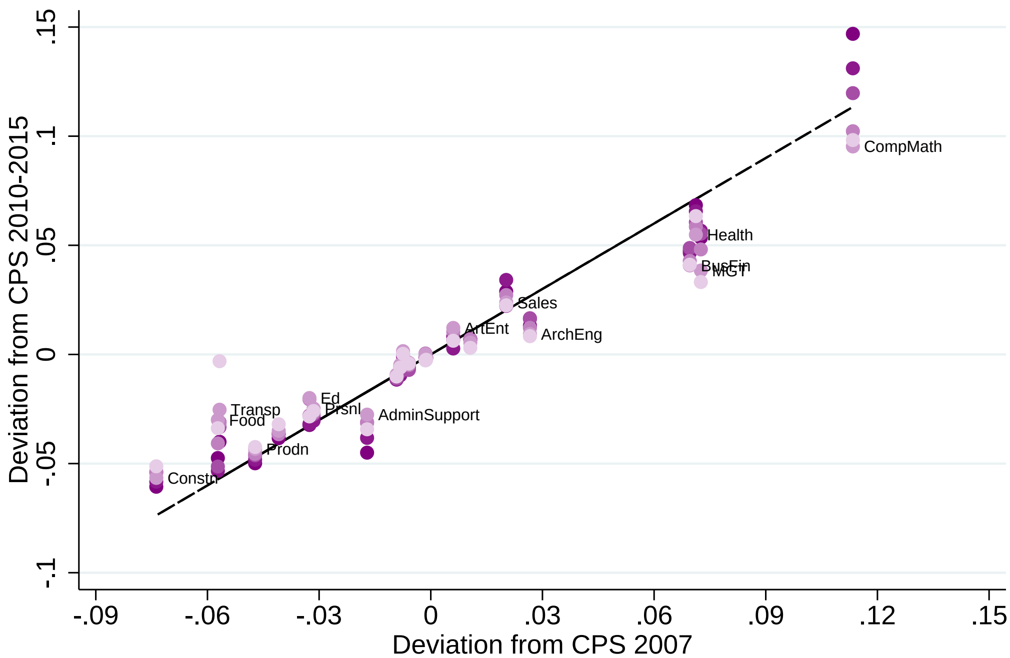


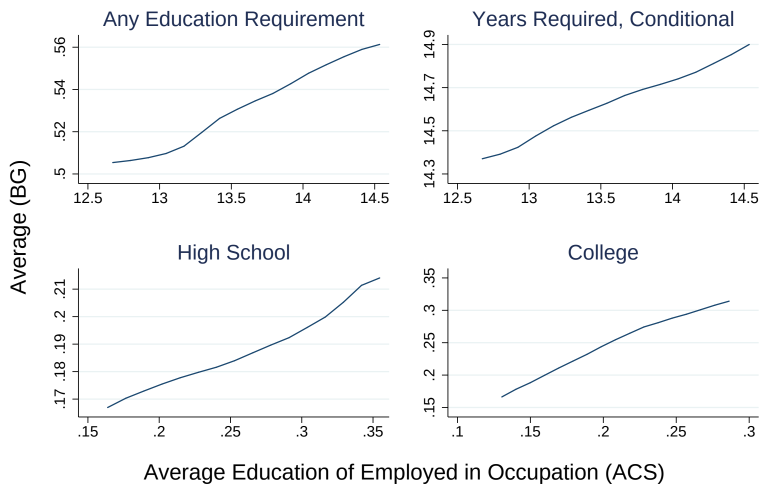
Figure A3: Representativeness of BG Occupations, Relative to New Jobs (CPS)



The x-axis is the BG ad share in an occupation in 2007 minus the CPS new job share in the same occupation in 2007. The y-axis is these differences for each year from 2010-2015. Darker shades are earlier years, lighter shades are later. As a benchmark, the 45 degree line (black dash) indicates occupations where representation in BG, relative to CPS, did not change from 2007.

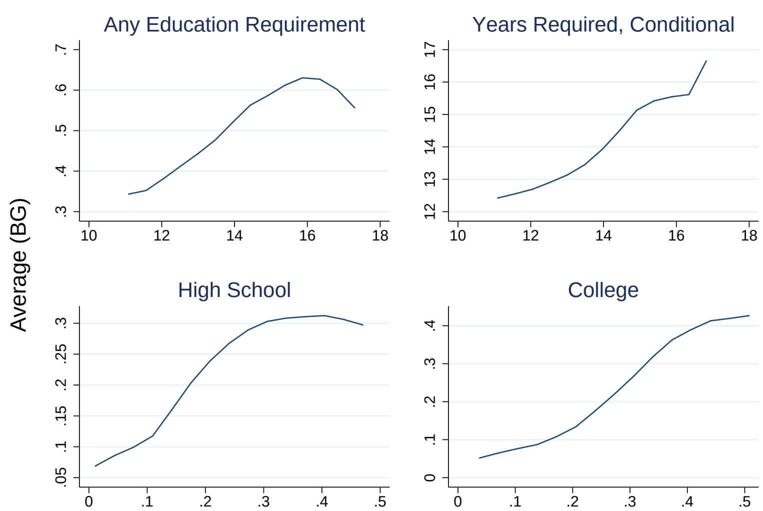
Figure A4: Comparison of BG Education Requirements and ACS Employment

(a) by MSA



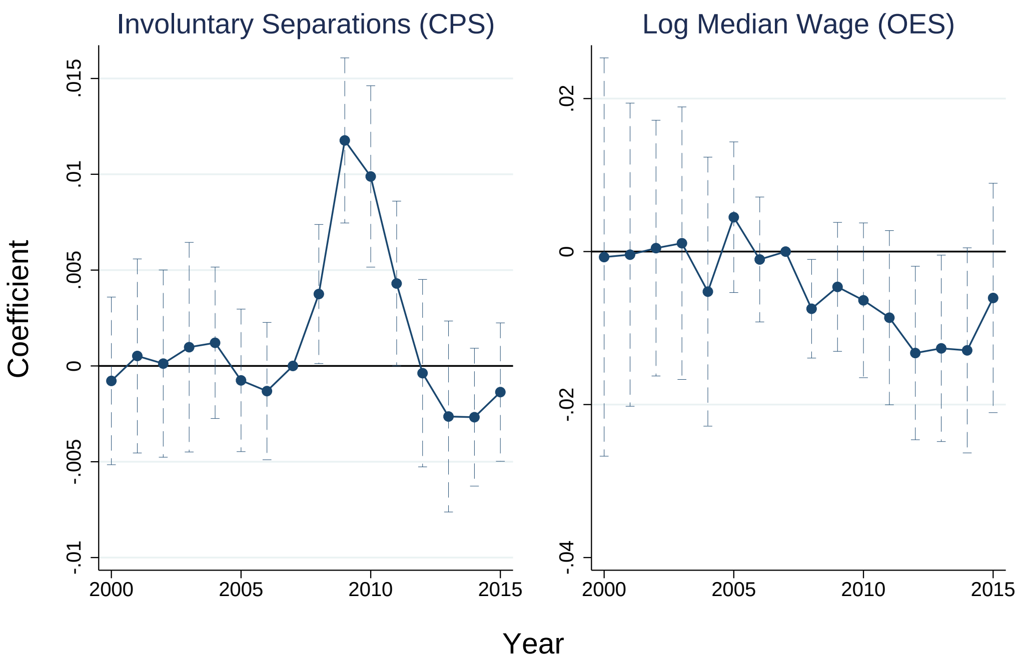
Smoothed local linear regression of occupation-level education requirement on ACS education percentile. Top panel uses average years of schooling for employed workers in the MSA as the ACS variable; BG variable is the share of ads with any education requirement (left) or average years required conditional on any (right). Bottom panel uses the share of employed workers with exactly a high school diploma (left) or college degree (right) as the ACS variable; BG variables are the share of ads requiring the specified degree.

(b) by Occupation



See notes to sub-figure (a). Here ACS variables are average education requirements in the occupation (instead of MSA).

Figure A5: Layoffs and Wages: Full Effects



We regress the MSA-level change in local labor market variables from 2007 on an exhaustive set of MSA employment shock-by-year interactions, controlling for year fixed effects (see equation 1). Graph plots the coefficients on Bartik shock*year, as well as 95% CI bars. Involuntary separations are author calculations based on the CPS. Log median wages obtained from Occupational Employment Statistics.

Table A1: Probability of Being Missing from a Subsample

	Burning Glass:					Harte Hanks:
	Change in Pr(Missing from):					
Dep Var:	*Firm Sample*	*2007-10 match*	*Firm pre-post match*	*Harte Hanks*	*Compustat*	*Site pre-recession match*
	(1)	(2)	(3)	(4)	(5)	(6)
*Shock*2000*						0.0148*
						(0.00781)
*Shock*2002*						0.00442
						(0.00585)
*Shock*2004*						0.00442
						(0.00585)
*Shock*2008*						0.00546
						(0.00671)
*Shock*2010*	-0.0273	0.0136	0.00921	-0.0146	-0.0139	0.0110
	(0.0178)	*(0.0146)*	*(0.0125)*	*(0.0147)*	*(0.0113)*	*(0.00927)*
*Shock*2011*	-0.0299	0.0246*	0.0199	-0.00598	-0.000753	
	(0.0184)	*(0.0141)*	*(0.0122)*	*(0.0154)*	*(0.00953)*	
*Shock*2012*	-0.0656***	0.0344**	0.0289**	0.00622	0.00165	0.00491
	(0.0195)	*(0.0161)*	*(0.0143)*	*(0.0153)*	*(0.00971)*	*(0.00935)*
*Shock*2013*	-0.0155	0.00923	0.00249	-0.00843	-0.00174	
	(0.0202)	*(0.0108)*	*(0.00889)*	*(0.0141)*	*(0.00999)*	
*Shock*2014*	0.00305	0.0102	0.00271	-0.0112	0.00618	0.00231
	(0.0269)	*(0.0127)*	*(0.0100)*	*(0.0144)*	*(0.00973)*	*(0.00974)*
*Shock*2015*	0.0269	-0.00140	-0.00764	-0.0186	0.00226	
	(0.0224)	*(0.0129)*	*(0.0111)*	*(0.0156)*	*(0.0108)*	
# MSA-Year Cells	2,286	2,286	2,286	2,286	2,286	2,667
R-Squared	0.265	0.584	0.689	0.428	0.355	0.985

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

Notes: Observations are MSA-year cells weighted by the MSA labor force in 2006; regressions also control for year effects and MSA characteristics; standard errors are clustered at the MSA level. We regress the change from 2007 (2006 in column 6) in the share of ads (site employment in column 6) not meeting the indicated sample criterion. Column 1 is estimated on the full BG sample of ads and examines the change in the probability of having a missing firm name. Columns 2-5 are estimated on our primary non-missing firm BG sample and examine the change in the probability of being missing from: the sample of firms that post at least 5 ads in 2007 and 2010 (column 2), the sample of firms that post in 2007 and a later year (column 3), the Harte Hanks firm match sample (column 4), the Compustat firm match sample (column 5). BG observations are restricted to 2010-2015. Column 6 examines the change in shares of employment that are in sites (akin to establishments) that can be matched to at least one year in 2002, 2004, or 2006, in the Harte Hanks sample.

B Additional Results

B.1 Education and Experience Intensive Margins

Appendix figure B1 summarizes results for additional education and experience outcomes in order to understand changes in the intensive margin for these requirements. The top two panels of figure B1a show similar-sized increases in the probability of requiring a high school diploma and the probability of requiring a bachelor's degree. These increases offset each other, resulting in no overall change in the years of education required, conditional on posting any requirement (bottom right panel). Also, there is no change in the propensity to require a graduate degree (bottom left panel). This last finding is reassuring, since many professional jobs, such as lawyers and professors, have long required postgraduate degrees; these requirements would not be expected to change with improvements in technology. Figure B1b exhibits a similar pattern for experience requirements. We observe increases in experience requirements at the low (2 years or less) and middle (3–5 years) parts of the distribution; there is little change at the high end. As with education, this pattern results in little net change in total years of experience required, conditional on posting any requirement.

Are these increases in requirements plausible? For example if increases in college (high school) requirements were found in typically very low- (high-) skilled jobs, we might worry about the quality of the data. In figure B2 we explore heterogeneity in upskilling effects as a function of the average years of schooling of workers in the occupation, as measured in the ACS in 2005–06, before the Great Recession. We estimate separate within-occupation upskilling regressions (equation (1) of the main text), by ventile of this occupational education variable, for the change in the propensity to specify a high school diploma (left) or bachelor's degree (right) requirement. We summarize these regression results by plotting the estimated coefficients on the Bartik shock for 2010 (blue, solid lines) and 2015 (maroon, dashed lines), smoothing the 20 estimates in each series with local linear regression.

Focusing first on the left panel, we find that increased demand for a high school credential is largest for occupations that tend to employ workers with less education before the recession. In fact, the strongest increases occur at the lowest ventiles, representing occupations whose workers have an average of about 11 years of schooling. Effects monotonically decline with the average education of occupations, and are essentially zero for occupations that typically employ college graduates. This pattern is highly consistent with the increased propensity to require a high school credential in job postings reflecting upskilling. It does not appear to be the case, for instance, that firms add the requirement to signal to workers that they do not need *even more* education.

The right panel shows that the increased propensity to require a bachelor's degree is concentrated in occupations that tend to employ workers with at least some some college, peaking for occupations that typically require a bachelor's degree (16 years). Requirement increases are non-existent for occupations that tend to employ high school graduates (12 years) or those with less education, and increases are smaller for occupations that tend to employ workers with post-graduate degrees (more than 16 years). This pattern of targeted increases in line with expectations is also reassuring that our estimates reflect upskilling. What's more, the persistence in upskilling in our main estimates shows up where it is expected, as the blue and maroon lines essentially overlap; it is not the case that increased requirements are temporarily concentrated in overly high (or low) parts of the distribution.

B.2 Robustness Checks

Tables B1-B4 provide a range of robustness checks to the main within-occupation upskilling regression results from table 2 of the main text. For each table, column 1 replicates the main result, and the remaining columns provide results from different specifications, discussed below.

Local labor market controls

In column 2, we control for additional MSA-level labor market variables. As noted in the text, controls proxying for the availability of labor across skill groups help to clarify the importance of opportunistic upskilling, as well as firm reactions to the availability of skilled labor, more broadly. We control for a wide range of labor market characteristics over our sample period, and changes in these characteristics from the previous decade. Specifically, drawing from the ACS, we include unemployment rates and employment-to-population ratios at the MSA level for five education groups (high school dropouts, high school graduates, those with some college, those with a BA, and those with more than a BA). To reduce measurement error from occasionally small samples, these rates and ratios are calculated as the average over 2005–07. Additionally, we include the change in the rates and ratios between 2005–07 and the current year-pair (2010–11, 2012–13, 2014–15), as well as the change between 2000 (using Census data) and 2005–07.

The results in column 2 include two additional sets of controls. The first are MSA-level quit rates and their changes, by education group, obtained from the CPS. Because the sample size of the CPS is much smaller than that of the ACS, we aggregate across broader education groups and pool more sample years. We distinguish between those with no more than a high school diploma and those with some college or more. Quit rates are averaged for each education group over 2005–07, and the changes are between 2005–07 and the current year-triple (2010–12, 2013–15), as well as between 2000–02 to 2005–07. The second set of controls complements the 2005–06 MSA characteristics already included in the main specification with the changes in these characteristics between 2000 and 2005–06: the share of the population that is female, black, Hispanic, Asian, married, migrated in the last year, is a high school drop out, has exactly a high school diploma, has some college, has exactly a bachelor's degree, is enrolled in school, is less than age 18, is age 19–29, is age 30–39, is age 40–49, is age 50–64, the overall employment-to-population ratio, and the average weekly wage of full-time workers. These changes are calculated using the ACS and 2000 Census, and we include a dummy to capture cases in which MSAs are not identifiable in the ACS or CPS.

As shown in column 2, the inclusion of all of these local labor market controls does not have a substantive impact on the estimates, which are either reduced by between one-tenth and one-fifth (education and experience) or are essentially changed or even slightly larger (cognitive and computer). We have also explored including only subsets of these additional controls (these estimates are not shown in the tables). When we include just the education-specific unemployment rates, employment-population ratios, and their changes, the estimates are generally reduced by between one-tenth and one-fifth, and sometimes slightly more in the earlier years of the sample. However, they remain significant in both magnitude and a statistical sense. When we include only education-specific quit rates and their changes, the estimates increase modestly from baseline. A possible explanation for this pattern is that we find that quit rates of less-educated workers rebound more quickly than that of more-educated workers. Replacement hiring would then shift toward lower skilled workers, absent these controls. Finally, when we include only changes in MSA characteristics (in addition to the levels included in baseline), the estimates fall by about one-fifth for education and experience and about one-tenth for cognitive; they do not change for computer. In no case, therefore, does the general picture of our baseline estimates change.

Occupation controls

As noted in the text, results are robust to the inclusion of occupation fixed effects and occupation-specific time trends to allow for the possibility that some occupations may be both upskilling at a faster rate and disproportionately located in harder-hit MSAs. These controls also help adjust for possible changes in the sample due to shifting occupational mix in the BG data. Column 3 shows that we obtain very similar results even when including occupation-specific controls.

Weights

Our baseline within-occupation upskilling regressions in table 2 of the main text weight cells by the product of the occupation's ad share in the MSA-year and the size of the MSA labor force in 2006. This procedure can reduce measurement error and attenuation bias by putting more weight on cells that have more ads while mitigating against the possible endogeneity of using the number of ads themselves as weights. However, if there are heterogeneous impacts of the shock on upskilling tied to the size of the MSA or occupation share, we may be identifying a local average treatment effect that may not hold across all cells. Column 4 of the robustness tables thus provides estimates when we instead allow equal weight across occupation-MSA-years, limiting the sample to the 99% of ads that are in cells with at least 15 ads. We obtain qualitatively similar results that are generally still statistically significant, although, consistent with the possibility of attenuation bias, reduced in magnitude in some cases. This pattern also holds for the overall MSA-year level regressions, as in figure 2 of the main text, and when we instead weight to match the occupation-MSA employment stock distribution in the OES or the national occupation flow (new employment) distribution in the CPS (not shown).

Ads with missing firm name

Our baseline results focus on the 60 percent of ads that contain firm name, as this sample allows us to distinguish among firm-level mechanisms for upskilling. One might be concerned, though, that ads with firm names have differentially changing skill requirements relative to ads without firm names, perhaps due to firm size, prestige, or use of a third-party recruiting firm. Column 5 shows the robustness of our results to using the full sample of ads, including those with missing firm names. Results on the expanded sample are quite similar for all dependent variables.[18]

Alternative Bartik employment shocks

Our preferred measure of the local labor demand shock, used for our baseline estimates, is the change in projected annual employment growth between 2006 and 2009 (equation (2) of the main text). Columns 6–8 of the tables provide results using three variants of the Bartik employment shock. Rather than using fixed peak and trough years for all MSAs, Column 6 instead allows for MSA-specific peak and trough dates, using the calendar month with the largest 12-month employment growth between 2005 and 2007 as the peak date, and the calendar month with the smallest 12-month employment growth from 2008 onwards as the trough date. Column 7 uses the change in projected employment *levels* between 2006 and 2009, rather than the change in projected employment *growth*.[19] Column 8 uses the change between the average projected one-month employment growth in 2006 and the average in 2009, rather than the change in annual employment growth between the two years. The results are not especially sensitive to using MSA-specific cycle timing (column 6) or short-run projected changes in employment growth (column 8). Using projected changes in employment levels as the shock measure (column 7) reduces the magnitude of the point estimates by about one-half, but they are still statistically significant and of meaningful

[18] We also find no systematic relationship between the change in the share of ads with a missing firm and our key explanatory variables. See column 1 of appendix table A1.

[19] We believe the latter approach better captures the suddenness of the shift in conditions between 2006 and 2009 as they pertain to flow employment, but the literature has sometimes used the levels approach (Bartik 1991). In practice, they are highly correlated, with an employment-weighted correlation of $r = 0.86$.

magnitude.

Industry Controls

In order to explore heterogeneity within and across industries, we disaggregate our data by industry (2-digit NAICS). Columns labeled 1 in table B5 estimate changes in skill requirements within industry-occupation cells as a function of the MSA employment shock.[20] We find that these estimates are very similar to the results presented in figure 2 and table 2 of the main text. Firms in harder-hit MSAs differentially increase skill requirements in job postings, and this effect holds true within industry-occupation cells.

The second column of table B5 adds industry fixed effects and industry-specific linear time trends, and our estimates are essentially unchanged. These controls are particularly important given our identification: the interaction of national changes in employment growth by three-digit NAICS industry and MSA-level industry composition. Suppose that the industries driving negative employment shocks are precisely those that experience contemporaneous technology shocks—and concomitant temporary employment declines during an adjustment period. In this case our results would not indicate that firms concentrated their adoption of *existing* technologies during recessions but rather that the occurrence of the innovations themselves was concentrated during the recession. The fact that our results obtain even within sector alleviates this concern. Allowing for what essentially amounts to a quadratic secular change in skill requirements for each sector (given our first differences specification), we still find quantitatively similar evidence of upskilling.

We also investigate whether upskilling is more pronounced in sectors producing locally-consumed goods and services. Unlike the tradable sector, the product demand for which is largely determined by markets farther away or diffused across many areas, firms producing locally-consumed goods and services are highly sensitive to local demand shocks, and thus should be more greatly affected by the variation we identify with the Bartik employment shock.

To classify sectors, we adopt Jensen and Kletzer's (2005) measure of the degree to which production is "offshorable," which is based on geographic concentration of employment in the industry. Intuitively, if employment for a sector can be geographically concentrated (e.g., software developers in Silicon Valley), then output for that sector is more likely traded and need not be consumed locally. From Jensen and Kletzer (2005), we obtain the share of employment in each two-digit NAICS sector that can be categorized as "*least* [geographically] concentrated," which we denote $local_s$.[21]

[20] As before, we weight each cell by the product of the size of the MSA's labor force in 2006 and the cell's ad share in each MSA-year, where the ad shares here are over industry-occupation groups. We require a match at the MSA-industry-occupation level between 2007 and at least one later year; this restrictions drops 6 percent of ads.

[21] Jensen and Kletzer (2005) measure geographic dispersion across MSAs of employment in detailed industry categories, and designate the category "least concentrated" to those industries with a Gini coefficient

We then estimate versions of equation (1) of the main text at the occupation-sector-MSA-year level that include sector fixed effects and allow for triple-interactions between the Bartik shock, year dummies, and $local_s$.

Figure B3 plots the estimates fitted at the 10th and 90th percentiles of $local_s$; these respectively capture the net upskilling effect for traded (dashed maroon line) and non-traded (solid blue line) sectors. With the exception of education, we find that increases in skill requirements are *larger* in the non-traded sectors, those in which local demand shocks should be the most salient for production.

B.3 Firm-Occupation Decomposition

We here explore the extent to which upskilling is driven by shifts in postings from old to new firms and changes within existing firms. By employing a formal decomposition, we investigate these margins simultaneously with shifts in ads across firms and those across occupations.[22]

Define C_t as the set of firm-MSAs that post ads in both year t and in 2007. We hereafter refer to these as "continuing firms," and the set of firm-MSAs that have posts only in 2007 or only in t as non-continuing firms. In our sample, 54 percent of weighted observations are to continuing firms.[23] We hope to understand the extent to which substitution across non-continuing firms versus changes within continuing firms affects overall changes in skill requirements.

In equation (1), we express the average skill requirement in MSA m and year t as a function of: p^C_{mt}, the share of ads in an MSA-year posted in continuing firms;[24] $\frac{N^C_{fmt}}{N^C_{mt}}$, the distribution of ads across continuing firms in mt; $\frac{N^C_{ofmt}}{N^C_{fmt}}$, the distribution of ads across occupations for a given continuing firm; $skill^C_{ofmt}$, the average skill requirement for continuing firm f, posting in occupation o, MSA m, and year t; $\frac{N^{NC}_{omt}}{N^{NC}_{mt}}$, the distribution of ads across occupations among non-continuing firms;[25] and$\bar{skill}^{NC}_{omt}$, the average skill requirement for occupation o, among all non-continuing firms in mt (that is, the average skill requirement in the occupation-MSA-year among firm-MSAs that posted either only in 2007 or only in period t).

less than 0.1. We have also used the measure from Blinder and Krueger (2013), based primarily on workers' survey responses on location requirements to do their jobs, to similar effect.

[22] Haltiwanger, Hyatt, Kahn and McEntarfer (2017) show that workers matching to jobs in downturns are more likely to match to low-paying firms than high-paying firms.

[23] Here we define "firm" as the group of ads with the same employer name in the same MSA, which allows us to take advantage of the cross-sectional variation in how MSAs bore the Great Recession. The set C_t is defined separately for each year from 2010–2015, though naturally there is substantial overlap in the set of continuing firms across years.

[24] By definition, $p^C_{mt} \equiv \frac{N^C_{mt}}{N^C_{mt}+N^{NC}_{mt}}$.

[25] Since, by definition, non-continuing firms cannot be matched across time periods, we aggregate over all non-continuing firms.

$$(1) \qquad skill_{mt} = p^C_{mt} \sum_{fm \in C_t} \sum_o \frac{N^C_{fmt}}{N^C_{mt}} \frac{N^C_{ofmt}}{N^C_{fmt}} * skill^C_{ofmt} + (1 - p^C_{mt}) \sum_o \frac{N^{NC}_{omt}}{N^{NC}_{mt}} s\bar{k}ill^{NC}_{omt}.$$

We then decompose the effect of the Bartik employment shock on the overall change in skill requirements at the MSA-year level ($skill_{mt} - skill_{m07}$), into effects attributable to changes in: p^C_{mt}, the share of ads in an MSA-year posted in continuing firms; $\frac{N^C_{fmt}}{N^C_{mt}}$, the distribution of ads across continuing firms in mt; $\frac{N^C_{ofmt}}{N^C_{fmt}}$, the distribution of ads across occupations for a given continuing firm; $skill^C_{ofmt}$, the average skill requirement for continuing firm f, posting in occupation o, MSA m, and year t; $\frac{N^{NC}_{omt}}{N^{NC}_{mt}}$, the distribution of ads across occupations among non-continuing firms; and$s\bar{k}ill^{NC}_{omt}$, the average skill requirement for occupation o, among all non-continuing firms in mt (that is, the average skill requirement in the occupation-MSA-year among firm-MSAs that posted either only in 2007 or only in period t).

In practice, this equation is not exact for two reasons. First, continuing firms do not necessarily post to the same set of occupations in each period (so $skill^C_{ofmt}$ would not be defined for some occupation-firm-MSA-year combinations but might be defined in, say, 2007). Second, the set of non-continuing firms does not post to the same set of occupations (so likewise $s\bar{k}ill^{NC}_{omt}$, which is the average skill requirement among all non-continuing firms posting in omt, would not be defined for some occupation-MSA-year combinations). To get around these issues, we simply aggregate up from the occupation-firm-MSA-year level to either the occupation-MSA-year level or the MSA-year level, the point where we get a match.

The exact definition is shown in equation (2).

$$(2) \qquad skill_{mt} = \begin{aligned} & p^C_{mt} * \pi^c_1 \sum_{fm \in C_t} \sum_{o \in CO^1} skill^{CO^1}_{ofmt} * \frac{N^{CO^1}_{ofmt}}{N^{CO^1}_{fmt}} \frac{N^{CO^1}_{fmt}}{N^{CO^1}_{mt}} \\ & + p^C_{mt} (\pi^c_2 \sum_{o \in CO^2} s\bar{k}ill^{CO^2}_{omt} * \frac{N^{CO^2}_{omt}}{N^{CO^1}_{mt}} + (1 - \pi^c_1 - \pi^c_2) s\bar{k}ill^{CO^3}_{mt}) \\ & + (1 - p^C_{mt})(\pi^{nc}_1 \sum_{o \in NCO^1} s\bar{k}ill^{NCO^1}_{omt} * \frac{N^{NCO^1}_{omt}}{N^{NCO^1}_{mt}} + (1 - \pi^{nc}_1) s\bar{k}ill^{NCO^2}_{mt}) \end{aligned}$$

In the top two lines, we divide the set of ads to continuing firms into three groups: occupations that are posted in a given firm-MSA in both t and in 2007 (the set CO^1), occupations that are not posted in a given firm-MSA in both periods but are posted among other continuing firms in both periods (CO^2), and occupations that are posted in one period by continuing firms but not in the other period (CO^3). The ad shares for these three groups (π^c_1, π^c_2, and $1 - \pi^c_1 - \pi^c_2$, respectively) sum to one within the set of ads to continuing firms (C_t).[26] Averaging across 2010–2015 in our data, 54 percent of weighted observations are to

[26] These weights vary by MSA-year, but subscripts are suppressed for clarity.

continuing firm-MSAs, of which 71 percent are to continuing occupations (CO^1), 28 percent are to non-continuing occupations that can still be matched to any other continuing firms (CO^2) and only 0.8 percent are to occupations that cannot be matched to any continuing firms (CO^3).

The first component, for continuing firm-occupations (CO^1) is straightforward and is defined by the within ofm average skill requirement ($skill^{CO^1}_{ofmt}$), the share of ads in this occupation, o, for the given fm ($\frac{N^{CO^1}_{ofmt}}{N^{CO^1}_{fmt}}$), and the share of all ads in CO^1 that are by firm f, ($\frac{N^{CO^1}_{fmt}}{N^{CO^1}_{mt}}$). The second components yields the average skill requirement among occupations by continuing firms that do not post for the same occupation in both periods. The idea is that we would like to compare the firm-occupation-specific requirement across years. However, in some cases continuing firms post in a new occupation in t, so the comparison is not available. Instead, we simply fix occupations and aggregate over firms. We can then ask whether skill requirements are more strenuous for continuing firms that enter into the occupation, relative to those that exited the occupation.[27] $\bar{skill}^{CO^2}_{omt}$ is the average skill requirement in occupation o among firm-MSAs that posted some ads in both periods, but posted in occupation o only in the given period, and $\frac{N^{CO^2}_{omt}}{N^{CO^1}_{mt}}$ is the ad share for the given occupation among all ads in the set (CO^2). Finally, the third component, $\bar{skill}^{CO^3}_{mt}$, is the average skill requirement in the MSA-year for ads posted by continuing firms in occupations that belong to neither CO^1 nor CO^2 (that is, an occupation where continuing firms either post only in 2007 or only in t).

In the third line of equation (2), we divide the set of ads to non-continuing firms into two groups: occupations that are posted in the MSA in both t and in 2007 (the set NCO^1) and those that are not (NCO^2), with weights π^{nc}_1 and $1 - \pi^{nc}_1$, respectively. Skill requirements for the former are a function of the within-occupation average skill requirement among all ads posted by non-continuing firms in mt in occupations that can be matched ($\bar{skill}^{NCO^1}_{omt}$) and the share of ads that are posted to occupation o, ($\frac{N^{NCO^1}_{omt}}{N^{NCO^1}_{mt}}$). The latter component is the average skill requirement among ads posted to non-continuing firms in mt in occupations that cannot be matched ($\bar{skill}^{NCO^2}_{mt}$). Of the 46 percent of weighted observations that are to non-continuing firms in our data, 97.5 percent of observations belong to the former (matched) group.

To decompose the change in skill requirements for a given MSA, m, from 2007 to a given year t ($skill_{mt} - skill_{m07}$) into these components we generate counterfactual differences that allow one component to change from its level in 2007 to its level in t, holding all other

[27] We could instead fix firms and aggregate over occupations. This allows us to ask whether the new occupations the firm enters into have different skill requirements than the occupations the firm left. However this yields far fewer matches, since it requires the firm-MSA to have at least one occupation it posted in 2007 but not t *and* at least one occupation it posted in t but not 2007. Many firm-MSAs either cease posting in some occupations after 2007 or begin posting to new occupations in t, but not both. Instead, aggregating over firms and fixing occupations requires that any continuing firm-MSA ceases posting in the occupation after 2007 and any continuing firm-MSA begins posting in the occupation in t.

components fixed at the level in either period.[28] We can regress this counterfactual skill change on the Bartik employment shock and the other controls in equation (1) of the main text to understand how much of the total responsiveness is attributed to a response in the within firm-MSA skill requirement.

A decomposition begins with $skill_{m07}$ and generates a counterfactual skill change distribution that allows only one of the components to vary. That component is then fixed at its value at time t and a second counterfactual skill change distribution is generated by allowing a second component to vary, keeping all components but the first two fixed at their 2007 level. This process continues until all components are at their time t values. We can regress each counterfactual change on the same variables in equation (1) of the main text, and the coefficients on $shock * I^t$ will sum to the coefficient on the full change reported earlier.

Naturally the order of the decomposition affects the relative importance of each component. For p components in the decomposition, we have $p!$ possible orders. To reduce the state space, we combine many of the variables in equation (2) into a smaller set of components since they turn out to be empirically irrelevant.

We reduce the space to six components, resulting in 720 possible permutations. We estimate each decomposition and summarize results in appendix table B6. Here we report the average fraction attributable to a given component, across all decompositions, as well as the standard deviation. The components are: (1) the share of ads among continuing firms, p^C_{mt}; (2) the distribution of ads across continuing firms that post in the same occupation in both periods, $\frac{N^{CO^1}_{ofmt}}{N^{CO^1}_{fmt}}$; (3) the within-firm-occupation skill requirement for continuing firms, $skill^{CO^1}_{ofmt}$; (4) the distribution of ads across occupations, which combines $\frac{N^{CO^1}_{ofmt}}{N^{CO^1}_{fmt}}, \frac{N^{CO^2}_{omt}}{N^{CO^2}_{mt}}, \frac{N^{NCO^1}_{omt}}{N^{NCO^1}_{mt}}$, π^c_1, π^c_2, and π^{nc}_1; (5) the skill requirement among continuing firms posting to occupations they had not previously posted in, which combines $skill^{CO^2}_{omt}$ and $\bar{skill}^{CO^3}_{mt}$; and (6) the skill requirement among non-continuing firms, which combines $\bar{skill}^{NCO^1}_{omt}$ and $\bar{skill}^{NCO^2}_{mt}$.

To summarize results from the table, we report the fraction of the overall impact of *shock* in the given year attributed to each component in figure B4. To make the graph easier to read, we combine some components together, focusing on the (empirically) most important.

The lightest bar shows the fraction of the overall upskilling effect in each year attributable to changes in the distribution of firms, combining the share of ads to continuing firms p^C_{mt} with the firm distribution among continuing firms $\frac{N^C_{fmt}}{N^C_{mt}}$. This combines columns 1 and 2 of table B6. The next lightest bar shows the fraction attributable to changes in the occupation distribution, combining the occupation distribution among continuing $(\frac{N^C_{ofmt}}{N^C_{fmt}})$ and non-continuing $(\frac{N^{NC}_{omt}}{N^{NC}_{mt}})$ firms. Across all dependent variables, we find that changes in

[28] For example, $p^C_{mt}(\pi^c_1 \sum_{fm \in C_t} \sum_{o \in CO^1} (skill^{CO^1}_{ofmt} - skill^{CO^1}_{ofm07}) * \frac{N^{CO^1}_{ofmt}}{N^{CO^1}_{fmt}} \frac{N^{CO^1}_{fmt}}{N^{CO^1}_{mt}}$ is the change in skill requirements between 2007 and t, attributed to just changes in the within occupation-firm-MSA skill requirements among continuing firms, holding constant all other components at their levels in t.

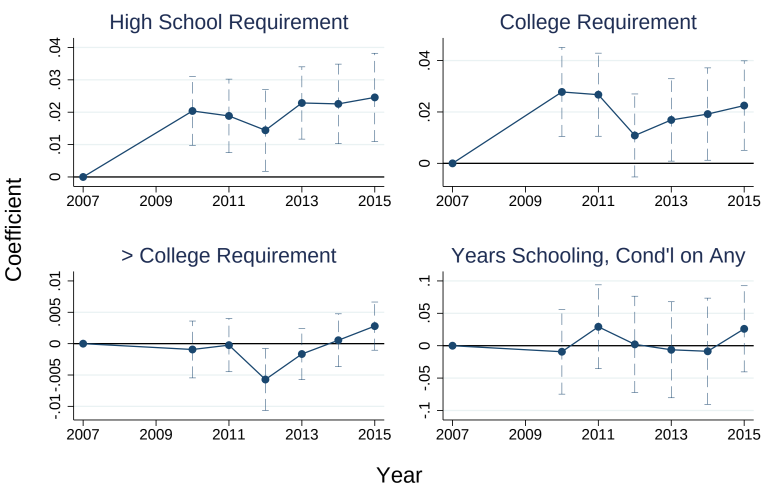
these firm and occupation distributions account for very little of the upskilling effects.

Instead, the vast majority of the upskilling effect is split across the two darker bars. The darkest bar shows the fraction attributable to changes in skill requirements of non-continuing firms for a given occupation ($s\bar{k}ill^{NC}_{omt}$). It compares, for each occupation, the skill requirements for firms that posted only in the later period (2010–2015) to the requirements for firms that stopped posting after 2007. The adjacent, next-darkest bars show the fraction attributable to the change in skill requirements between 2007 and t among continuing firm-MSAs. This combines columns 3 and 5 of table B6.[29] Across dependent variables and years, each of these two components contributes to roughly half of the upskilling effect.

[29] That is, this component includes both the change in skill requirements within firm-occupation-MSAs for firms that posted in a given *occupation* in both periods, and changes in skill requirements driven by continuing firm-MSAs that post for different occupations. Empirically, we find that both are important; the former is more important for education and experience requirements, while the two are roughly equally important for cognitive and computer requirements.

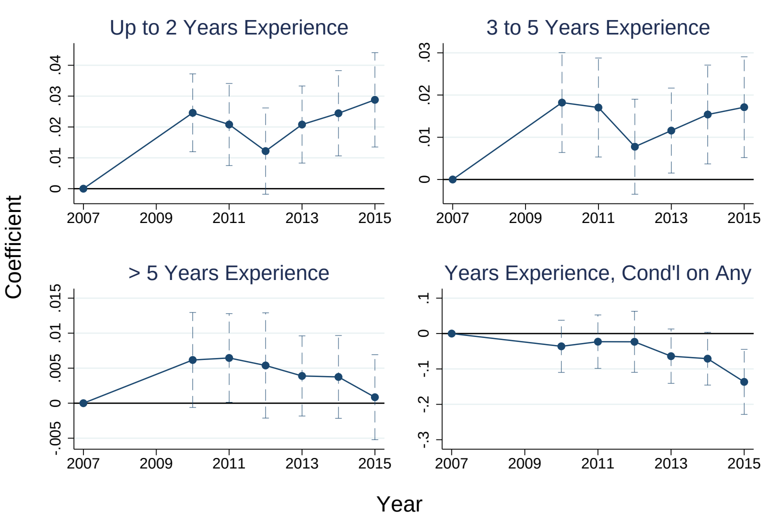
Figure B1: Impact of MSA-Specific Employment Shock on Education Requirements

(a) Education Requirements



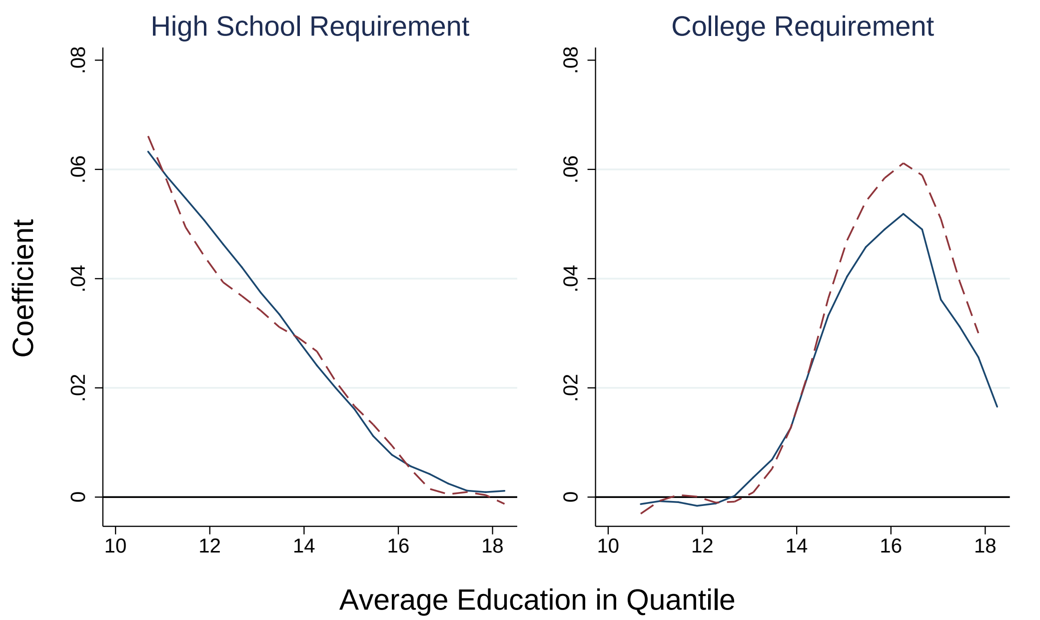
Dependent variables are the occupation-MSA change in the share of ads requiring exactly a high school diploma (top left), college degree (top right), more than a college degree (bottom left), or the average years required conditional on any (bottom right). We regress the occupation-MSA change in BG skill requirements from 2007 on an exhaustive set of MSA employment shock-by-year interactions, controlling for year fixed effects and MSA characteristics (see equation 1). Graph plots the coefficients on Bartik shock*year and 95% CIs.

(b) Experience Requirements



See sub-figure (a). Dependent variables are the occupation-MSA change in the share of ads requiring up to 2 years experience (top left), 3 to 5 years (top right), more than 5 years (bottom left), or the average years required conditional on any (bottom right).

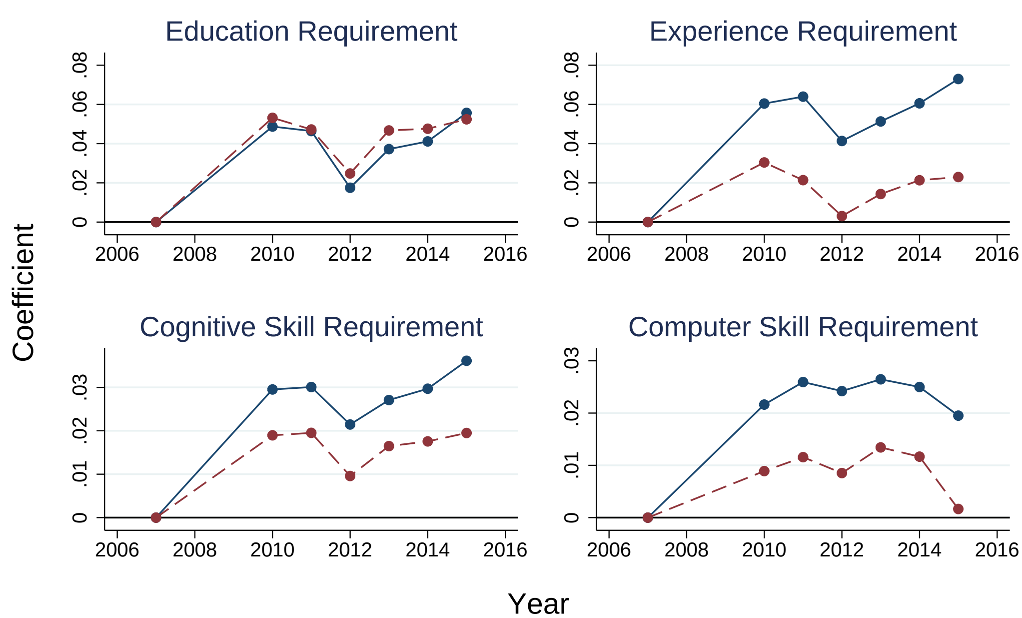
Figure B2: Change in Requirement by Occupation Education



Blue solid = 2007-2010 change, Maroon dash = 2007-2015.

We estimate separate within-occupation upskilling regressions for each ventile of the average years of schooling in the occupation (ACS 2005-06 average). Dependent variables are the change in the probability of specifying a high school diploma (left) or a college degree (right). We plot the coefficients on the Bartik*2010 and Bartik*2015 year interactions for each ventile and smooth with local linear regression. Regressions also control for year fixed effects and MSA characteristics.

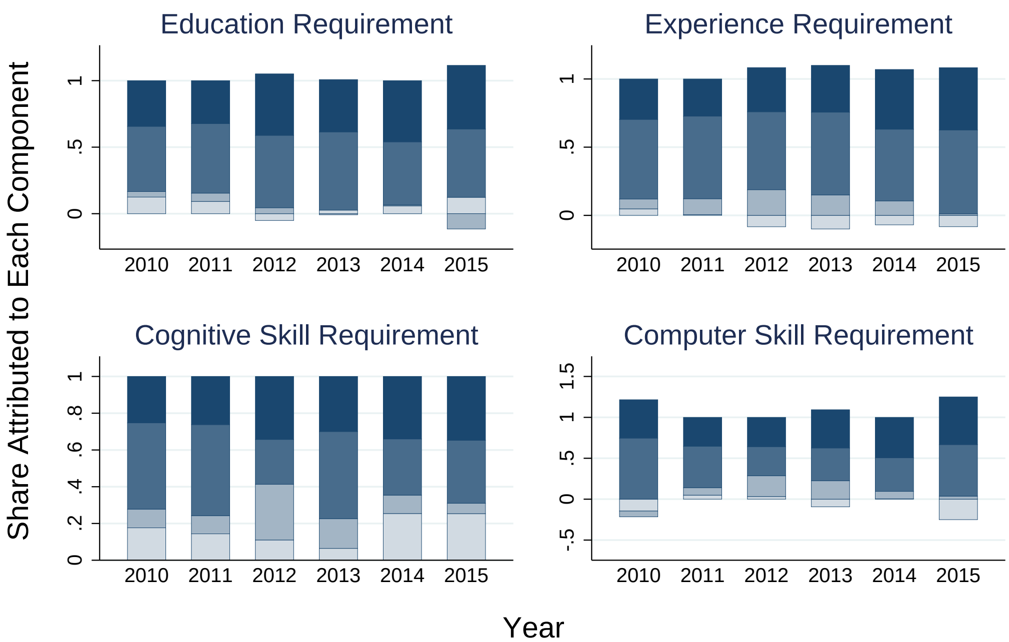
Figure B3: Upskilling by Sector Tradability



Blue line = local products, Maroon dashed line = traded products

We regress the industry-MSA change in BG skill requirements from 2007 on an exhaustive set of MSA employment shock-by-year interactions, and triple interactions between the shock, year, and offshorability. We also control for year fixed effects and MSA characteristics. Graph plots the coefficients on the triple interactions. The offshorability measure is the 90-10 differential in the Jensen-Kletzer geographic employment concentration index.

Figure B4: Decomposing Upskilling Into Within and Across Firm Components



Darkest = old-new firms within occ, dark = within continuing firms, light = occ dist, lightest = firm dist

We decompose the impact of the MSA-specific Bartik employment shock on the change in skill requirements from 2007 in each year. We then plot the share attributed to each component, averaged across all possible decomposition orders.

Table B1: Robustness Checks: Education Requirement

Dependent Variable:	*Education Requirement*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*Shock*2010*	0.0526***	0.0528***	0.0516***	0.0333***	0.0429***	0.0521***	0.0317***	0.0465***
	(0.0135)	*(0.0148)*	*(0.0128)*	*(0.0126)*	*(0.0126)*	*(0.0132)*	*(0.0118)*	*(0.0130)*
*Shock*2011*	0.0475***	0.0477***	0.0462***	0.0316**	0.0359***	0.0483***	0.0278**	0.0423***
	(0.0131)	*(0.0144)*	*(0.0126)*	*(0.0122)*	*(0.0119)*	*(0.0126)*	*(0.0112)*	*(0.0124)*
*Shock*2012*	0.0233*	0.0251*	0.0226*	0.0177	0.0212*	0.0241**	0.00731	0.0243**
	(0.0128)	*(0.0145)*	*(0.0124)*	*(0.0114)*	*(0.0121)*	*(0.0120)*	*(0.0115)*	*(0.0121)*
*Shock*2013*	0.0400***	0.0423***	0.0406***	0.0274***	0.0343***	0.0403***	0.0215*	0.0359***
	(0.0120)	*(0.0131)*	*(0.0114)*	*(0.0101)*	*(0.0120)*	*(0.0116)*	*(0.0110)*	*(0.0116)*
*Shock*2014*	0.0429***	0.0424***	0.0440***	0.0280**	0.0320**	0.0427***	0.0218*	0.0374***
	(0.0143)	*(0.0140)*	*(0.0136)*	*(0.0112)*	*(0.0144)*	*(0.0136)*	*(0.0131)*	*(0.0141)*
*Shock*2015*	0.0488***	0.0483***	0.0532***	0.0200**	0.0327**	0.0483***	0.0291**	0.0413***
	(0.0143)	*(0.0149)*	*(0.0141)*	*(0.0101)*	*(0.0142)*	*(0.0140)*	*(0.0122)*	*(0.0135)*
# Occ-MSA-Year Cells	193,086	193,086	193,086	139,172	222,058	193,086	193,086	193,086
R-Squared	0.044	0.072	0.373	0.010	0.072	0.045	0.042	0.044
Labor Market Controls		X						
Occ FE and time trends			X					
Unweighted				X				
Includes Missing Firms					X			
Bartik w MSA-specific Peaks/Troughs						X		
Bartik in levels							X	
1 month employment change Bartik								X

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

Notes: Column 1 replicates estimates reported in table 2 of the text. The dependent variable is the occupation-MSA change in the indicated BG skill variable from 2007. All regressions control for year fixed effects and MSA characteristics from the ACS. Column 2 includes the change in the MSA characteristics from 2000 to 2005/6, as well as MSA-level education-specific employment, unemployment, and quit rates in 2005-07, the change in these variables from 2005-07 to the current year, and the change in these variables from 2000-02 to 2005-07. Column 3 includes occupation fixed effects and occupation-specific linear time trends. Column 4 presents unweighted regressions (each occupation-MSA cell gets the same weight) and restricts to cells with at least 15 ads. Column 5 includes all ads, not restricting to those with non-missing firms. Column 6 defines the MSA employment shock using MSA-specific peak and trough years, rather than imposing 2006 and 2009, respectively, for all MSAs. Column 7 defines the MSA employment shock as the projected change in log employment from 2006 to 2009, rather than the projected change in employment growth). Column 8 defines the employment shock as the one-month change in employment growth, rather than year-over-year change. All shock variables are divided by the 90-10 differential in the variable across all MSAs.

Table B2: Robustness Checks: Experience Requirement

Dependent Variable:	*Experience Requirement*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*Shock*2010*	0.0490***	0.0453***	0.0486***	0.0295***	0.0442***	0.0495***	0.0263**	0.0435***
	(0.0134)	*(0.0138)*	*(0.0130)*	*(0.0102)*	*(0.0138)*	*(0.0130)*	*(0.0115)*	*(0.0131)*
*Shock*2011*	0.0443***	0.0406***	0.0435***	0.0245**	0.0340***	0.0459***	0.0237**	0.0406***
	(0.0134)	*(0.0142)*	*(0.0133)*	*(0.0106)*	*(0.0129)*	*(0.0129)*	*(0.0114)*	*(0.0129)*
*Shock*2012*	0.0253*	0.0257*	0.0244*	0.0139	0.0199	0.0266**	0.00502	0.0275**
	(0.0136)	*(0.0148)*	*(0.0134)*	*(0.0105)*	*(0.0136)*	*(0.0129)*	*(0.0119)*	*(0.0129)*
*Shock*2013*	0.0363***	0.0370***	0.0356***	0.0172*	0.0312**	0.0366***	0.0174	0.0345***
	(0.0122)	*(0.0131)*	*(0.0121)*	*(0.00881)*	*(0.0124)*	*(0.0118)*	*(0.0108)*	*(0.0119)*
*Shock*2014*	0.0436***	0.0418***	0.0434***	0.0206**	0.0303**	0.0431***	0.0223*	0.0404***
	(0.0140)	*(0.0137)*	*(0.0137)*	*(0.00963)*	*(0.0139)*	*(0.0133)*	*(0.0126)*	*(0.0140)*
*Shock*2015*	0.0468***	0.0450***	0.0480***	0.0150*	0.0328**	0.0463***	0.0326***	0.0431***
	(0.0142)	*(0.0152)*	*(0.0139)*	*(0.00866)*	*(0.0147)*	*(0.0137)*	*(0.0124)*	*(0.0140)*
# Cells	193,086	193,086	193,086	139,172	222,058	193,086	193,086	193,086
R-Squared	0.069	0.102	0.354	0.011	0.102	0.069	0.066	0.068
Labor Market Controls		X						
Occ FE and time trends			X					
Unweighted				X				
Includes Missing Firms					X			
Bartik w MSA-specific Peaks/Troughs						X		
Bartik in levels							X	
1 month employment change Bartik								X

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

Notes: See table 2 and appendix table B1.

Table B3: Robustness Checks: Cognitive Skill Requirement

Dependent Variable:	*Cognitive Skill Requirement*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*Shock*2010*	0.0275***	0.0242***	0.0270***	0.0120*	0.0173**	0.0262***	0.0161**	0.0236***
	(0.00726)	*(0.00785)*	*(0.00674)*	*(0.00655)*	*(0.00711)*	*(0.00702)*	*(0.00641)*	*(0.00687)*
*Shock*2011*	0.0281***	0.0248***	0.0272***	0.0166***	0.0200***	0.0272***	0.0151**	0.0258***
	(0.00731)	*(0.00754)*	*(0.00682)*	*(0.00600)*	*(0.00652)*	*(0.00707)*	*(0.00635)*	*(0.00731)*
*Shock*2012*	0.0186***	0.0161**	0.0182***	0.0117**	0.0141**	0.0175***	0.0102	0.0177***
	(0.00693)	*(0.00764)*	*(0.00648)*	*(0.00574)*	*(0.00596)*	*(0.00662)*	*(0.00644)*	*(0.00660)*
*Shock*2013*	0.0253***	0.0229***	0.0248***	0.0163***	0.0165***	0.0242***	0.0136**	0.0221***
	(0.00642)	*(0.00687)*	*(0.00625)*	*(0.00540)*	*(0.00564)*	*(0.00625)*	*(0.00599)*	*(0.00622)*
*Shock*2014*	0.0265***	0.0242***	0.0268***	0.0154***	0.0174***	0.0251***	0.0154**	0.0245***
	(0.00657)	*(0.00678)*	*(0.00635)*	*(0.00520)*	*(0.00630)*	*(0.00622)*	*(0.00601)*	*(0.00655)*
*Shock*2015*	0.0300***	0.0278***	0.0320***	0.0171***	0.0243***	0.0284***	0.0156**	0.0260***
	(0.00730)	*(0.00766)*	*(0.00711)*	*(0.00518)*	*(0.00777)*	*(0.00713)*	*(0.00642)*	*(0.00733)*
# Cells	178,176	178,176	178,176	135,878	207,552	178,176	178,176	178,176
R-Squared	0.040	0.050	0.287	0.006	0.075	0.040	0.039	0.040
Labor Market Controls		X						
Occ FE and time trends			X					
Unweighted				X				
Includes Missing Firms					X			
Bartik w MSA-specific Peaks/Troughs						X		
Bartik in levels							X	
1 month employment change Bartik								X

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

Notes: See table 2 and appendix table B1.

Table B4: Robustness Checks: Computer Skill Requirement

Dependent Variable:	*Computer Skill Requirement*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*Shock*2010*	0.0203**	0.0217***	0.0212***	0.0183***	0.0181**	0.0206**	0.00715	0.0163*
	(0.00859)	*(0.00777)*	*(0.00742)*	*(0.00605)*	*(0.00784)*	*(0.00816)*	*(0.00753)*	*(0.00871)*
*Shock*2011*	0.0243***	0.0257***	0.0241***	0.0206***	0.0244***	0.0248***	0.0131**	0.0214***
	(0.00716)	*(0.00661)*	*(0.00647)*	*(0.00617)*	*(0.00694)*	*(0.00687)*	*(0.00641)*	*(0.00722)*
*Shock*2012*	0.0207**	0.0235***	0.0205***	0.0199***	0.0224***	0.0209***	0.0112	0.0196**
	(0.00848)	*(0.00817)*	*(0.00766)*	*(0.00622)*	*(0.00740)*	*(0.00803)*	*(0.00764)*	*(0.00844)*
*Shock*2013*	0.0252***	0.0283***	0.0250***	0.0250***	0.0260***	0.0252***	0.0114*	0.0225***
	(0.00664)	*(0.00587)*	*(0.00596)*	*(0.00567)*	*(0.00649)*	*(0.00624)*	*(0.00606)*	*(0.00702)*
*Shock*2014*	0.0227***	0.0246***	0.0233***	0.0234***	0.0188***	0.0224***	0.0118*	0.0205***
	(0.00679)	*(0.00653)*	*(0.00612)*	*(0.00586)*	*(0.00709)*	*(0.00626)*	*(0.00637)*	*(0.00713)*
*Shock*2015*	0.0134*	0.0153**	0.0155**	0.0224***	0.0134*	0.0136*	0.00582	0.00936
	(0.00807)	*(0.00722)*	*(0.00778)*	*(0.00497)*	*(0.00703)*	*(0.00759)*	*(0.00780)*	*(0.00808)*
# Cells	178,176	178,176	178,176	135,878	207,552	178,176	178,176	178,176
R-Squared	0.034	0.049	0.292	0.008	0.055	0.035	0.033	0.034
Labor Market Controls		X						
Occ FE and time trends			X					
Unweighted				X				
Includes Missing Firms					X			
Bartik w MSA-specific Peaks/Troughs						X		
Bartik in levels							X	
1 month employment change Bartik								X

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

Notes: See table 2 and appendix table B1.

Table B5: Within-Industry-Occupation Effects

Dependent Variable:	Education		Experience		Cognitive Skill		Computer Skill	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
*Shock*2010*	0.0514***	0.0493***	0.0489***	0.0477***	0.0248***	0.0257***	0.0194**	0.0164*
	(0.0146)	*(0.0144)*	*(0.0152)*	*(0.0148)*	*(0.00838)*	*(0.00811)*	*(0.00928)*	*(0.00859)*
*Shock*2011*	*0.0468****	*0.0454****	*0.0466****	*0.0457****	*0.0258****	*0.0263****	*0.0234****	*0.0200****
	(0.0142)	*(0.0142)*	*(0.0150)*	*(0.0150)*	*(0.00810)*	*(0.00809)*	*(0.00797)*	*(0.00758)*
*Shock*2012*	*0.0214*	*0.0199*	*0.0274**	*0.0259**	*0.0163***	*0.0170***	*0.0213***	*0.0180**
	(0.0141)	*(0.0140)*	*(0.0152)*	*(0.0151)*	*(0.00777)*	*(0.00775)*	*(0.00992)*	*(0.00939)*
*Shock*2013*	*0.0400****	*0.0411****	*0.0372****	*0.0377****	*0.0230****	*0.0231****	*0.0247****	*0.0218****
	(0.0135)	*(0.0134)*	*(0.0138)*	*(0.0138)*	*(0.00702)*	*(0.00704)*	*(0.00791)*	*(0.00757)*
*Shock*2014*	*0.0434****	*0.0442****	*0.0466****	*0.0467****	*0.0249****	*0.0249****	*0.0231****	*0.0204****
	(0.0157)	*(0.0154)*	*(0.0156)*	*(0.0154)*	*(0.00739)*	*(0.00739)*	*(0.00821)*	*(0.00784)*
*Shock*2015*	*0.0505****	*0.0559****	*0.0500****	*0.0552****	*0.0280****	*0.0293****	*0.0129*	*0.0129*
	(0.0157)	*(0.0162)*	*(0.0156)*	*(0.0158)*	*(0.00816)*	*(0.00820)*	*(0.00948)*	*(0.00921)*
Industry FE and trends		X		X		X		X

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

Notes: See table 2. Regressions are estimated at the MSA-occupation (4-digit SOC)-industry (2-digit NAICS) year level. The dependent variable is the MSA-occupation-industry level annual change in skill requirements from 2007. All regressions control for year fixed effects and MSA characteristics from the ACS. Observations are weighted by the size of the MSA labor force in 2006 multiplied by the cell's ad share in the MSA-year. Standard errors are clustered at the MSA level.

Table B6: Decomposing Upskilling Within and Across Firms and Occupations

Share of coeff attributed to:	Education Requirements (1)	(2)	(3)	(4)	(5)	(6)	Experience Requirements (1)	(2)	(3)	(4)	(5)	(6)
Shock*2010	0.070	0.055	0.415	0.042	0.075	0.343	-0.007	0.055	0.460	0.072	0.124	0.296
	(0.152)	(0.010)	(0.086)	(0.040)	(0.024)	(0.159)	(0.129)	(0.097)	(0.152)	(0.051)	(0.046)	(0.130)
Shock*2011	0.046	0.046	0.471	0.062	0.052	0.323	-0.037	0.043	0.465	0.116	0.140	0.273
	(0.154)	(0.008)	(0.122)	(0.042)	(0.036)	(0.136)	(0.138)	(0.046)	(0.134)	(0.063)	(0.049)	(0.122)
Shock*2012	-0.031	-0.020	0.613	0.045	-0.069	0.462	-0.091	0.008	0.553	0.188	0.018	0.324
	(0.342)	(0.040)	(0.320)	(0.133)	(0.067)	(0.273)	(0.253)	(0.105)	(0.307)	(0.093)	(0.066)	(0.196)
Shock*2013	0.041	-0.014	0.503	-0.008	0.085	0.394	-0.017	-0.083	0.508	0.150	0.099	0.343
	(0.142)	(0.029)	(0.090)	(0.074)	(0.066)	(0.129)	(0.146)	(0.064)	(0.137)	(0.107)	(0.075)	(0.120)
Shock*2014	0.085	-0.026	0.367	0.007	0.107	0.460	0.003	-0.072	0.436	0.106	0.090	0.438
	(0.169)	(0.031)	(0.056)	(0.061)	(0.051)	(0.186)	(0.175)	(0.064)	(0.119)	(0.064)	(0.048)	(0.176)
Shock*2015	0.192	-0.069	0.319	-0.115	0.195	0.479	0.063	-0.146	0.419	0.012	0.196	0.457
	(0.174)	(0.023)	(0.031)	(0.040)	(0.044)	(0.179)	(0.168)	(0.144)	(0.172)	(0.066)	(0.056)	(0.169)
Share of coeff attributed to:	**Cognitive Skill Requirements (1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**Computer Skill Requirements (1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Shock*2010	0.025	0.151	0.388	0.102	0.082	0.252	-0.184	0.039	0.550	-0.070	0.196	0.469
	(0.117)	(0.032)	(0.087)	(0.069)	(0.067)	(0.106)	(0.190)	(0.062)	(0.117)	(0.165)	(0.153)	(0.185)
Shock*2011	0.037	0.106	0.429	0.099	0.067	0.262	-0.039	0.088	0.371	0.090	0.137	0.353
	(0.144)	(0.043)	(0.155)	(0.068)	(0.049)	(0.123)	(0.174)	(0.069)	(0.110)	(0.110)	(0.087)	(0.172)
Shock*2012	-0.010	0.120	0.267	0.303	-0.023	0.343	-0.008	0.040	0.283	0.254	0.073	0.358
	(0.222)	(0.128)	(0.238)	(0.074)	(0.038)	(0.192)	(0.210)	((0.073)	(0.135)	(0.147)	(0.102)	(0.205)
Shock*2013	0.069	-0.005	0.376	0.162	0.098	0.300	-0.032	-0.061	0.224	0.225	0.177	0.468
	(0.150)	(0.114)	(0.165)	(0.132)	(0.089)	(0.115)	(0.230)	(0.041)	(0.059)	(0.214)	(0.139)	(0.195)
Shock*2014	0.212	0.042	0.216	0.100	0.089	0.340	0.056	-0.052	0.194	0.091	0.217	0.494
	(0.156)	(0.130)	(0.128)	(0.071)	(0.045)	(0.141)	(0.206)	(0.047)	(0.047)	(0.184)	(0.154)	(0.200)
Shock*2015	0.177	0.076	0.244	0.057	0.099	0.347	0.075	-0.325	0.201	0.037	0.429	0.584
	(0.127)	(0.042)	(0.053)	(0.060)	(0.016)	(0.122)	(0.265)	(0.084)	(0.135)	(0.255)	(0.182)	(0.133)

Notes: The table gives the share of the coefficient listed in the left column attributed to a change in the component labeled in the top row, averaged across 720 decomposition orders and the standard deviation across all orders in parentheses. Components are: (1) share of ads to continuing firm-MSAs, (2) firm distribution among continuing firms, (3) within firm-occupation-MSA skill requirement, (4) the distribution of ads across occupations, (5) the within-occupation skill requirement among continuing firms in non-continuing occupations, (6) within-occupation skill requirement among non-continuing firms.

C Tables Corresponding to Figures in the Text

Table C1: MSA-Level Outcomes and the Employment Shock

Dep Var:	Emp Growth	Unemp Rate	Epop College	Epop High School	Burning-Glass Skills: Education	Experience	Cognitive	Computer	PCs (HH)	Employment Shares: Routine-Cog	Routine-Man
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
*Shock*2000*	0.00698	-0.00509*	0.0216	0.00757					0.525	-0.00806	0.000161
	(0.00470)	*(0.00285)*	*(0.0132)*	*(0.0110)*					*(0.370)*	*(0.00798)*	*(0.0114)*
*Shock*2001*	-0.000397	-0.000366	0.0161	0.00340						-0.00605	-0.00314
	(0.00599)	*(0.00219)*	*(0.0119)*	*(0.0100)*						*(0.00477)*	*(0.0104)*
*Shock*2002*	-0.00202	0.000992	-0.00504	-0.00131					0.469	-0.0108	-0.000681
	(0.00776)	*(0.00320)*	*(0.0113)*	*(0.0106)*					*(0.367)*	*(0.00718)*	*(0.0118)*
*Shock*2003*	0.00252	0.00101	0.00371	0.00375						-0.00578	-0.00501
	(0.00664)	*(0.00297)*	*(0.0104)*	*(0.0101)*						*(0.00577)*	*(0.0104)*
*Shock*2004*	0.0121*	0.000207	-0.00414	0.00507					0.458	-0.00545*	0.000119
	(0.00631)	*(0.00189)*	*(0.00928)*	*(0.00972)*					*(0.367)*	*(0.00330)*	*(0.0112)*
*Shock*2005*	0.0177***	0.000221	-0.00882	0.0131*						-0.00486	-0.000883
	(0.00554)	*(0.00166)*	*(0.00853)*	*(0.00678)*						*(0.00343)*	*(0.00342)*
*Shock*2006*	0.0154***	-0.00112	-0.000365	0.0103**						-0.00274	0.000531
	(0.00416)	*(0.00127)*	*(0.00620)*	*(0.00507)*						*(0.00258)*	*(0.00358)*
*Shock*2008*	-0.0172***	0.00597***	-0.0144**	-0.00846					1.318***	-0.00139	-0.00521
	(0.00233)	*(0.00162)*	*(0.00681)*	*(0.00670)*					*(0.451)*	*(0.00252)*	*(0.00329)*
*Shock*2009*	-0.0383***	0.0226***	-0.0345***	-0.0114						0.00309	-0.0158***
	(0.00355)	*(0.00320)*	*(0.00867)*	*(0.00770)*						*(0.00367)*	*(0.00334)*
*Shock*2010*	-0.00904**	0.0202***	-0.0332***	-0.0120	0.0540***	0.0503***	0.0280***	0.0171	1.800**	0.00451	-0.0206***
	(0.00439)	*(0.00318)*	*(0.0110)*	*(0.00740)*	*(0.0133)*	*(0.0136)*	*(0.00815)*	*(0.0137)*	*(0.877)*	*(0.00416)*	*(0.00375)*
*Shock*2011*	0.00488	0.0140***	-0.0235**	-0.0153*	0.0474***	0.0463***	0.0293***	0.0264***		0.00640*	-0.0210***
	(0.00355)	*(0.00359)*	*(0.0114)*	*(0.00849)*	*(0.0129)*	*(0.0131)*	*(0.00746)*	*(0.00812)*		*(0.00336)*	*(0.00423)*
*Shock*2012*	0.0108***	0.00350	-0.0265*	-0.00473	0.0210	0.0265**	0.0186**	0.0267**	1.316**	0.00580*	-0.0183***
	(0.00327)	*(0.00429)*	*(0.0137)*	*(0.00905)*	*(0.0130)*	*(0.0133)*	*(0.00732)*	*(0.0108)*	*(0.647)*	*(0.00319)*	*(0.00425)*
*Shock*2013*	0.0120***	0.000300	-0.0169	-0.00140	0.0364***	0.0360***	0.0253***	0.0281***		0.00607**	-0.0175***
	(0.00354)	*(0.00307)*	*(0.0141)*	*(0.0100)*	*(0.0117)*	*(0.0121)*	*(0.00662)*	*(0.00792)*		*(0.00291)*	*(0.00440)*
*Shock*2014*	0.0121***	-0.00102	-0.00861	-0.00485	0.0386***	0.0417***	0.0277***	0.0234***	1.010	0.00745**	-0.0139***
	(0.00385)	*(0.00237)*	*(0.0115)*	*(0.0109)*	*(0.0144)*	*(0.0142)*	*(0.00695)*	*(0.00794)*	*(1.063)*	*(0.00293)*	*(0.00467)*
*Shock*2015*	0.00953**	-0.00234	-0.0129	-0.00757	0.0416***	0.0433***	0.0319***	0.0136*		0.0110***	-0.0110**
	(0.00430)	*(0.00223)*	*(0.0110)*	*(0.0111)*	*(0.0141)*	*(0.0144)*	*(0.00754)*	*(0.00817)*		*(0.00359)*	*(0.00473)*
# MSA-Year Cells	5,714	5,715	2,833	2,833	2,286	2,286	2,286	2,286	2,667	4,530	4,530
R-Squared	0.535	0.764	0.394	0.336	0.207	0.291	0.337	0.319	0.050	0.257	0.500

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

Notes: Columns 1-4 correspond to figure 1, columns 5-8 to figure 2, column 9 to figure 4, and columns 10-11 to the top right panel of figure 7. See equation 1. The dependent variable is the MSA-level annual change in the indicated variable from 2007 (2006 in column 9) -- there are at most 381 distinct MSAs. All regressions control for year fixed effects (columns 5-11 also controls for MSA characteristics). Observations are weighted by the size of the MSA labor force in 2006 and standard errors are clustered at the MSA level. Shock is the change in projected year-over-year employment growth in the MSA from 2006 to 2009, divided by the 90-10 differential in the variable across all MSAs. Employment growth and unemployment rates (columns 1 and 2) obtained directly from BLS. Epops (columns 3 and 4) are author calculations based on the CPS -- there are fewer MSAs available in the CPS. Columns 1-4 estimate changes in local labor market variables from 2007 for all other years from 2000-2015. Skill requirements (columns 5-8) from BG are restricted to 2010-2015. PCs per average pre-recession employment (column 9) is obtained from Harte Hanks; these regressions include only even years. Routine-cognitive and -manual employment shares (columns 10 and 11, respectively) are obtained from OES, and are available in all years. Routine-cognitive (manual) occupations are those in the top quartile of the routine-cognitive (manual) index of Acemoglu and Autor.

Table C2: Differential Upskilling by 90-10 Change in Firm Capital Investments

	PCs (HH)				Capital Holdings (Compustat)			
Dependent Variable:	*Education* (1)	*Experience* (2)	*Cognitive* (3)	*Computer* (4)	*Education* (1)	*Experience* (2)	*Cognitive* (3)	*Computer* (4)
*Capital*Shock*2010*	0.00697***	0.00398***	0.00155*	0.00606***	0.00246***	0.00232***	0.000672	0.00286***
	(0.00124)	*(0.00118)*	*(0.000914)*	*(0.00107)*	*(0.000402)*	*(0.000311)*	*(0.000519)*	*(0.000256)*
*Capital*Shock*2011*	0.00567***	0.00246*	0.00116	0.00527***	0.00265***	0.00309***	0.00113*	0.00265***
	(0.00122)	*(0.00140)*	*(0.00100)*	*(0.00119)*	*(0.000577)*	*(0.000422)*	*(0.000577)*	*(0.000374)*
*Capital*Shock*2012*	0.00598***	0.00352***	0.00121	0.00565***	0.00254***	0.00316***	0.00132**	0.00233***
	(0.00100)	*(0.00103)*	*(0.00105)*	*(0.00119)*	*(0.000552)*	*(0.000428)*	*(0.000539)*	*(0.000352)*
*Capital*Shock*2013*	0.00956***	0.00710***	0.00223*	0.00509***	0.00335***	0.00366***	0.00152***	0.00283***
	(0.00155)	*(0.00145)*	*(0.00123)*	*(0.00104)*	*(0.000314)*	*(0.000323)*	*(0.000497)*	*(0.000297)*
*Capital*Shock*2014*	0.0101***	0.00718***	0.00552***	0.00761***	0.00312***	0.00340***	0.00145**	0.00290***
	(0.00149)	*(0.00162)*	*(0.00167)*	*(0.00112)*	*(0.000652)*	*(0.000665)*	*(0.000611)*	*(0.000441)*
*Capital*Shock*2015*	0.0108***	0.00390**	0.00424***	0.00541***	0.00216***	0.00271***	0.00110*	0.00270***
	(0.00141)	*(0.00164)*	*(0.00161)*	*(0.00129)*	*(0.000588)*	*(0.000554)*	*(0.000640)*	*(0.000318)*
*Shock*2010*	0.0234	0.0180	0.00867	0.0140	0.0129	-0.00132	0.00467	0.00356
	(0.0182)	*(0.0166)*	*(0.00842)*	*(0.0101)*	*(0.0196)*	*(0.0169)*	*(0.0103)*	*(0.0110)*
*Shock*2011*	0.0295*	0.0308*	0.00815	0.0202**	0.0316*	0.0206	0.00982	0.0252***
	(0.0169)	*(0.0170)*	*(0.00880)*	*(0.00954)*	*(0.0184)*	*(0.0186)*	*(0.0102)*	*(0.00898)*
*Shock*2012*	0.0106	0.00895	0.00202	0.0213*	0.0117	0.00343	0.00364	0.0235**
	(0.0181)	*(0.0188)*	*(0.00915)*	*(0.0112)*	*(0.0221)*	*(0.0200)*	*(0.00997)*	*(0.0111)*
*Shock*2013*	0.0191	0.0129	-0.00402	0.0169	0.0315	0.0192	-0.00422	0.0213**
	(0.0173)	*(0.0184)*	*(0.00862)*	*(0.0110)*	*(0.0212)*	*(0.0226)*	*(0.00887)*	*(0.00961)*
*Shock*2014*	0.0271	0.0319	-0.00345	0.0182*	0.0388	0.0410*	0.000217	0.0142
	(0.0197)	*(0.0194)*	*(0.00977)*	*(0.00997)*	*(0.0238)*	*(0.0235)*	*(0.0114)*	*(0.0107)*
*Shock*2015*	0.0259	0.0220	0.0112	0.0133	0.0290	0.0382*	0.00726	0.0148
	(0.0185)	*(0.0175)*	*(0.0102)*	*(0.0107)*	*(0.0225)*	*(0.0203)*	*(0.0118)*	*(0.0122)*
# Firm-MSA-Year Cells	492,291	492,291	445,856	445,856	236,783	236,783	218,254	218,254
R-Squared	0.019	0.019	0.009	0.010	0.029	0.035	0.015	0.023

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

Notes: Columns 1-4 correspond to figure 5a and columns 5-8 correspond to figure 5b. The dependent variable is the firm-MSA-level annual change in the indicated BG skill requirement from 2007. All regressions control for year fixed effects and MSA characteristics. Observations are weighted by the size of the MSA labor force in 2006 times the firm's ad share within the MSA-year and standard errors are clustered at the MSA level. Shock is the change in projected year-over-year employment growth in the MSA from 2006 to 2009, divided by the 90-10 differential in the variable across all MSAs. Capital variable is the firm-level average change PCs per employee from 2002-2006 to 2010-2014 (columns 1-4) from Harte Hanks or the firm-level average rate of change of capital holdings (property plant and equipment) over the same years (columns 5-8) from Compustat. Capital variables have been normed to be mean 0 so the main shock-year variables fit the effect for the average firm. Figures 5a and 5b fit capital-shock-year interactions to the 90-10 firm differential -- therefore coefficients are multiplied by 0.97 (columns 1-4) or 2.27 (columns 5-8).

Table C3: Differential Upskilling for Routine Occupations

	Routine-Cognitive				Routine-Manual			
Dependent Variable:	*Education*	*Experience*	*Cognitive*	*Computer*	*Education*	*Experience*	*Cognitive*	*Computer*
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
*Routine*Shock*2010*	0.00496***	0.00368***	0.00532***	0.0157***	0.00835***	0.00311**	-0.00580***	-0.0152***
	(0.00182)	*(0.000657)*	*(0.000611)*	*(0.000683)*	*(0.00146)*	*(0.00138)*	*(0.00109)*	*(0.000951)*
*Routine*Shock*2011*	0.00721***	0.00467***	0.00838***	0.0139***	0.00382***	-0.000845	-0.00817***	-0.0124***
	(0.00122)	*(0.000685)*	*(0.000634)*	*(0.000883)*	*(0.00126)*	*(0.000993)*	*(0.00106)*	*(0.00102)*
*Routine*Shock*2012*	0.00940***	0.00275***	0.00792***	0.0100***	0.00177	-0.00264***	-0.0112***	-0.0145***
	(0.00106)	*(0.000772)*	*(0.000551)*	*(0.000906)*	*(0.00121)*	*(0.00101)*	*(0.00104)*	*(0.000999)*
*Routine*Shock*2013*	0.0122***	0.00781***	0.00820***	0.0106***	-0.00191**	-0.00367***	-0.0118***	-0.0117***
	(0.000874)	*(0.000741)*	*(0.000481)*	*(0.000715)*	*(0.000903)*	*(0.000883)*	*(0.00103)*	*(0.00106)*
*Routine*Shock*2014*	0.0130***	0.00972***	0.0101***	0.0100***	-0.00262**	-0.00159	-0.0117***	-0.0109***
	(0.00119)	*(0.000788)*	*(0.000472)*	*(0.000707)*	*(0.00101)*	*(0.000983)*	*(0.000960)*	*(0.00106)*
*Routine*Shock*2015*	0.00940***	0.00102	0.00777***	0.00825***	-0.00250**	-0.00231***	-0.00843***	-0.0123***
	(0.00147)	*(0.000731)*	*(0.000699)*	*(0.000933)*	*(0.00113)*	*(0.000887)*	*(0.00111)*	*(0.00104)*
*Shock*2010*	0.0514***	0.0481***	0.0263***	0.0167**	0.0516***	0.0486***	0.0280***	0.0218**
	(0.0136)	*(0.0134)*	*(0.00717)*	*(0.00799)*	*(0.0135)*	*(0.0134)*	*(0.00728)*	*(0.00858)*
*Shock*2011*	0.0457***	0.0431***	0.0260***	0.0207***	0.0470***	0.0444***	0.0289***	0.0256***
	(0.0130)	*(0.0133)*	*(0.00716)*	*(0.00692)*	*(0.0131)*	*(0.0134)*	*(0.00735)*	*(0.00719)*
*Shock*2012*	0.0204	0.0245*	0.0162**	0.0176**	0.0230*	0.0257*	0.0202***	0.0228***
	(0.0127)	*(0.0135)*	*(0.00681)*	*(0.00825)*	*(0.0128)*	*(0.0135)*	*(0.00697)*	*(0.00851)*
*Shock*2013*	0.0364***	0.0340***	0.0229***	0.0220***	0.0403***	0.0368***	0.0270***	0.0268***
	(0.0120)	*(0.0122)*	*(0.00637)*	*(0.00645)*	*(0.0120)*	*(0.0122)*	*(0.00642)*	*(0.00666)*
*Shock*2014*	0.0393***	0.0409***	0.0237***	0.0199***	0.0433***	0.0438***	0.0281***	0.0242***
	(0.0143)	*(0.0140)*	*(0.00650)*	*(0.00662)*	*(0.0144)*	*(0.0140)*	*(0.00660)*	*(0.00680)*
*Shock*2015*	0.0464***	0.0465***	0.0281***	0.0113	0.0492***	0.0471***	0.0312***	0.0151*
	(0.0143)	*(0.0142)*	*(0.00722)*	*(0.00798)*	*(0.0144)*	*(0.0142)*	*(0.00733)*	*(0.00810)*
# Firm-MSA-Year Cells	193,086	193,086	178,176	178,176	193,086	193,086	178,176	178,176
R-Squared	0.057	0.073	0.054	0.064	0.045	0.069	0.045	0.043

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

Notes: Figure 6 plots the routine-shock-year interactions. The dependent variable is the occupation-MSA-level annual change in the indicated BG skill requirement from 2007. All regressions control for year fixed effects and MSA characteristics. Observations are weighted by the size of the MSA labor force in 2006 times the occupation's ad share within the MSA-year and standard errors are clustered at the MSA level. Shock is the change in projected year-over-year employment growth in the MSA from 2006 to 2009, divided by the 90-10 differential in the variable across all MSAs. "Routine" interactions in the left (right) panel are for routine-cognitive (routine-manual) occupations. These variables are an indicator for whether the occupation is in the top quartile of the routine-cognitive or routine-manual index of Acemoglu and Autor (2011).

Table C4: Differential Employment and Wage Effects for Routine Occupations

	Routine-Cognitive		Routine-Manual	
Dependent Variable:	Involuntary Separations	*Log(Median Wages)*	Involuntary Separations	*Log(Median Wages)*
	(1)	(2)	(1)	(2)
*Routine*Shock*2000*	-0.000161 *(0.000238)*	0.00166** *(0.000741)*	-0.00135*** *(0.000502)*	0.0137*** *(0.000980)*
*Routine*Shock*2001*	*0.000465** *(0.000262)*	*0.00256**** *(0.000682)*	*0.000866* *(0.000579)*	*0.0126**** *(0.000963)*
*Routine*Shock*2002*	*0.00147**** *(0.000314)*	*0.00207*** *(0.000824)*	*0.00162*** *(0.000675)*	*0.0101**** *(0.00112)*
*Routine*Shock*2003*	*0.00124**** *(0.000291)*	*0.00138*** *(0.000671)*	*0.00232**** *(0.000587)*	*0.00826**** *(0.00119)*
*Routine*Shock*2004*	*0.00110**** *(0.000293)*	*0.00289**** *(0.000580)*	*0.000660* *(0.000412)*	*0.00423**** *(0.00105)*
*Routine*Shock*2005*	*0.000555**** *(0.000205)*	*0.00332**** *(0.000494)*	*-5.04e-06* *(0.000458)*	*0.00322**** *(0.000539)*
*Routine*Shock*2006*	*-4.54e-06* *(0.000189)*	*0.00113**** *(0.000237)*	*-0.000419* *(0.000335)*	*0.000535* *(0.000427)*
*Routine*Shock*2008*	*0.000638**** *(0.000227)*	*0.000156* *(0.000259)*	*0.00394**** *(0.000422)*	*0.000512* *(0.000328)*
*Routine*Shock*2009*	*0.00295**** *(0.000423)*	*0.00136**** *(0.000246)*	*0.0155**** *(0.000739)*	*0.00239**** *(0.000569)*
*Routine*Shock*2010*	*0.00306**** *(0.000432)*	*0.000301* *(0.000418)*	*0.0138**** *(0.000672)*	*0.000659* *(0.000631)*
*Routine*Shock*2011*	0.00341*** *(0.000409)*	0.00107* *(0.000558)*	0.00957*** *(0.000653)*	0.000347 *(0.000690)*
*Routine*Shock*2012*	0.00249*** *(0.000332)*	0.00231*** *(0.000542)*	0.00662*** *(0.000625)*	9.11e-05 *(0.000657)*
*Routine*Shock*2013*	0.00182*** *(0.000307)*	0.00375*** *(0.000566)*	0.00382*** *(0.000655)*	-0.000514 *(0.000733)*
*Routine*Shock*2014*	0.00140*** *(0.000248)*	0.00480*** *(0.000553)*	0.00158*** *(0.000548)*	-0.000455 *(0.000894)*
*Routine*Shock*2015*	0.000242 *(0.000244)*	0.00507*** *(0.000659)*	-3.94e-05 *(0.000429)*	1.04e-05 *(0.000841)*
*Shock*2000*	*-0.000694* *(0.00223)*	*-0.00118* *(0.0133)*	*-0.000130* *(0.00225)*	*-0.00743* *(0.0134)*
*Shock*2001*	*0.000453* *(0.00258)*	*-0.00110* *(0.0101)*	*0.000517* *(0.00254)*	*-0.00632* *(0.0101)*
*Shock*2002*	*-0.000182* *(0.00250)*	*-8.73e-05* *(0.00855)*	*-6.77e-05* *(0.00244)*	*-0.00426* *(0.00840)*
*Shock*2003*	*0.000735* *(0.00277)*	*0.000687* *(0.00912)*	*0.000634* *(0.00274)*	*-0.00255* *(0.00885)*
*Shock*2004*	*0.00101* *(0.00201)*	*-0.00601* *(0.00894)*	*0.00132* *(0.00204)*	*-0.00703* *(0.00882)*
*Shock*2005*	*-0.000844* *(0.00189)*	*0.00363* *(0.00498)*	*-0.000463* *(0.00191)*	*0.00314* *(0.00504)*
*Shock*2006*	*-0.00128* *(0.00182)*	*-0.00137* *(0.00416)*	*-0.000899* *(0.00186)*	*-0.00105* *(0.00423)*
*Shock*2008*	*0.00366*** *(0.00184)*	*-0.00757*** *(0.00329)*	*0.00302* *(0.00184)*	*-0.00746*** *(0.00335)*
*Shock*2009*	*0.0112**** *(0.00220)*	*-0.00505* *(0.00428)*	*0.00829**** *(0.00226)*	*-0.00536* *(0.00438)*
*Shock*2010*	0.00933*** *(0.00241)*	-0.00651 *(0.00516)*	0.00689*** *(0.00244)*	-0.00637 *(0.00521)*
*Shock*2011*	0.00364* *(0.00219)*	-0.00901 *(0.00581)*	0.00239 *(0.00221)*	-0.00852 *(0.00582)*
*Shock*2012*	-0.000811 *(0.00252)*	-0.0140** *(0.00578)*	-0.00152 *(0.00251)*	-0.0130** *(0.00575)*
*Shock*2013*	-0.00295 *(0.00255)*	-0.0138** *(0.00620)*	-0.00322 *(0.00250)*	-0.0122** *(0.00618)*
*Shock*2014*	-0.00293 *(0.00183)*	-0.0144** *(0.00680)*	-0.00276 *(0.00182)*	-0.0125* *(0.00690)*
*Shock*2015*	-0.00137 *(0.00184)*	-0.00763 *(0.00756)*	-0.00106 *(0.00184)*	-0.00581 *(0.00777)*
# Occ-MSA-Year Cells	226,191	376,897	226,191	376,897
R-Squared	0.029	0.607	0.049	0.610

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

Notes: Figure 7 (top left and bottom right panels) plots the routine-shock-year interactions. The dependent variable is the occupation-MSA-level annual change in the indicated variable from 2007. All regressions control for year fixed effects and MSA characteristics. Observations are weighted by the size of the MSA labor force in 2006 times the occupation's ad share within the MSA-year and standard errors are clustered at the MSA level. Shock is the change in projected year-over-year employment growth in the MSA from 2006 to 2009, divided by the 90-10 differential in the variable across all MSAs. "Routine" interactions in the left (right) panel are for routine-cognitive (routine-manual) occupations. These variables are an indicator for whether the occupation is in the top quartile of the routine-cognitive or routine-manual index of Acemoglu and Autor. Involuntary separations are based on author calculations from the CPS. Log median wage is obtained from OES.

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