American Economic Review 2018, 108(7): 1737–1772
https://doi.org/10.1257/aer.20161570

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

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We show that skill requirements in job vacancy postings differentially increased in MSAs that were hit hard by the Great Recession, relative to less hard-hit areas. These increases persist through at least the end of 2015 and are correlated with increases in capital investments, both at the MSA and firm levels. We also find that effects are most pronounced in routine-cognitive occupations, which exhibit relative wage growth as well. We argue that this evidence is consistent with the restructuring of production toward routine-biased technologies and the more-skilled workers that complement them, and that the Great Recession accelerated this process. (*JEL* E24, E32, J24, J31, J63, L23, O33)

The employment shift from occupations in the middle of the skill distribution toward those in the tails is one of the most important trends in the US labor market over the last 30 years. Previous research makes the compelling case that a primary driver of this job polarization is routine-biased technological change (RBTC), whereby new machine technologies and overseas labor substitute for middle-skill jobs in the United States and are in turn complementary to high-skill cognitive jobs.[1] Until recently, RBTC had been thought to be a gradual, secular phenomenon. However, a long theoretical literature, beginning with Schumpeter's (1939) "creative destruction," suggests adjustments to technological change may be more episodic. In boom times, high opportunity costs, or frictions such as adjustment costs, may inhibit resources from being reallocated optimally in the face of technological

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[†] Go to https://doi.org/10.1257/aer.20161570 to visit the article page for additional materials and author disclosure statement(s).

[1] See, for example, the seminal work of Autor, Levy, and Murnane (2003); Goos and Manning (2007); Autor, Katz, and Kearney (2008); and Autor and Dorn (2013).

change. Recessions lower the opportunity cost and can produce large enough shocks to overcome these frictions.[2]

Whether adjustments to new technology are smooth or lumpy is important for policy and for our understanding of recoveries. The recoveries from the last three US recessions (1991, 2001, 2007–2009) have been jobless: employment was slow to rebound despite recovery in aggregate output. The reasons for jobless recovery are not well understood, but a small theoretical literature points to adjustment costs as a potential mechanism, since they can generate reallocation that is concentrated in downturns (Koenders and Rogerson 2005; Berger 2012; Jaimovich and Siu 2012). Such lumpy adjustment may leave a mass of displaced workers with the wrong skills for new production. Jaimovich and Siu (2015) provide suggestive evidence that countercyclical reallocation, in the form of RBTC, and jobless recovery are linked. They show that the vast majority of the declines in middle-skill employment have occurred during recessions and that, over the same time period, recovery was jobless only in these occupations. However, there is still relatively little direct evidence on how firms restructure employment in the face of technological change, and, in particular, whether this restructuring is gradual or episodic.[3]

In this paper we investigate how the demand for skills changed over the Great Recession. We use a new dataset collected by Burning Glass Technologies that contains the near-universe of electronically posted job vacancies in 2007 and 2010–2015. Exploiting spatial variation in economic conditions, we establish a new fact: the skill requirements of job ads increase in metropolitan statistical areas (MSAs) that suffered larger employment shocks in the Great Recession, relative to the same areas before the shock and other areas that experienced smaller shocks. Our estimates imply that ads posted in a hard-hit metro area are about 5 percentage points (16 percent) more likely to contain education and experience requirements and about 2–3 percentage points (8–12 percent) more likely to state requirements for cognitive and computer skills. Moreover, the vast majority of this "upskilling" persists through the end of our sample in 2015. That is, even while most measures of local labor-market strength had converged back to pre-recession levels, differences in advertised skill demands remain. This is true holding constant a rich set of controls for the availability of skilled labor and the composition of ads across firms and occupations. In fact, we find that the very firms that upskilled early in the recovery drive the persistence later in our sample period.

These patterns collectively raise the possibility that a structural shift in the demand for skill occurred disproportionately in harder-hit MSAs. In particular, the skill requirements we explore (education, experience, cognitive, and computer) are known to complement routine-biased technologies (Autor, Levy, and Murnane 2003; Brynjolfsson and McAfee 2011). If a structural shift in line with RBTC is occurring, we would expect changes in these skill requirements to be accompanied by an

[2]Many theoretical papers predict this phenomenon. See, for example, Hall (1991, 2005); Caballero and Hammour (1994, 1996); Mortensen and Pissarides (1994); Gomes, Greenwood, and Rebelo (2001); and Koenders and Rogerson (2005).

[3]For example, Acemoglu and Restrepo (2017) find that the diffusion of industrial robots across US commuting zones reduced aggregate employment and wages; Harrigan, Reshef, and Toubal (2016) show that job polarization was more pronounced in French firms with greater shares of technology-related occupations; and Hawkins, Michaels, and Oh (2015) show that capital investments and employment reductions frequently occur together in Korean manufacturing plants, but these papers focus on long-run changes.

accelerated adoption of such technologies, as well. Indeed, we find that increases in skill requirements are correlated with capital investments at both the MSA and firm levels. First, using the Ci Technology Database from Harte-Hanks, a market intelligence firm, we show that harder-hit MSAs exhibited a relative increase in IT investments, as measured by the adoption of personal computers, at the same time as they upskilled in job postings. These differences across MSAs emerge only after the Great Recession and, once again, persist through our sample period. Second, we link firms in our job postings database to those in the Harte-Hanks database, as well as to publicly traded firms in Compustat. We show that the firms increasing their capital investments, based on PC adoption and physical capital holdings, are also more likely to upskill. Thus, increased demand for labor skill appears closely linked to both general and IT capital investment.

If this increased investment is in fact related to routine-biased technologies, we would expect to see the strongest changes to labor characteristics for the jobs most susceptible to such technologies, routine ones. We thus additionally focus on different types of routine occupations, exploring joint changes in skill requirements, employment, and wages. Following Acemoglu and Autor (2011), we distinguish routine-cognitive occupations (e.g., clerical, administrative, and sales) from routine-manual ones (e.g., production and operatives), and we supplement the job ads data with Current Population Survey (CPS) and Occupational Employment Statistics (OES) data. For routine-manual occupations, we see evidence consistent with firms' substitution of technology for labor: a sharp increase in layoff risk for harder-hit MSAs early on, and persistently depressed employment, with no particular impact on skill requirements. This is the traditional view exhibited in the polarization literature: employment losses concentrated in occupations we expect to be most readily replaceable by machines. Consistent with Jaimovich and Siu (2015), we show that these changes also appear to be episodic around the Great Recession. However, in contrast to this conventional view of labor substitution, routine-cognitive occupations in harder-hit MSAs surprisingly exhibit only modest increases in layoff risk and no relative employment losses. Instead, we show that these occupations experience pronounced upskilling, as well as modest relative wage and employment growth after the recession. That is, rather than disappearing entirely, surviving routine-cognitive occupations appear to have become both relatively higher-skilled and more productive. These occupations thus became episodically less routine, and more cognitive, as a result of the Great Recession.

Taken together, our results suggest that firms located in areas more severely affected by the Great Recession were induced to restructure their production toward greater use of technology and higher-skilled workers; that is, the Great Recession hastened the polarization of the US labor market.

This paper is related to a number of important literatures. First, we provide evidence that the Great Recession spurred persistent changes in labor inputs, in a manner consistent with technological change. Several classes of models with adjustment costs can rationalize this result. For instance, firms may make productivity-enhancing improvements in a recession because of a decline in the opportunity cost of restructuring (Hall 2005), a shift in managerial attention from growth to efficiency possibly due to an increased risk of closure (Koenders and Rogerson 2005; Gibbons and Roberts 2012), or changes in the costs and benefits of making layoffs (Berger 2012; Jaimovich and Siu 2012). In addition, recessions may drive Schumpeterian cleansing, whereby older, less-productive firms die, making way for newer, more-productive firms. Empirical support for adjustment-cost models has focused on the impacts of competition or trade shocks on productivity. For example, Bloom, Draca, and Van Reenen (2016) show that increased Chinese import competition in Europe led to technological change within firms.[4] Our paper adds to this literature by highlighting recession-induced changes in the firm-level demand for skill. This may have important consequences for labor market recoveries, since it implies potential for a sudden skill mismatch.

Second, the Burning Glass job postings data provide a unique opportunity to measure changes in skill requirements both across and *within* occupations. In contrast, the extant literature on job polarization has focused on shifts across occupations and has therefore been unable to ascertain the importance of the intra-occupational margin. We show that the bulk of upskilling occurs within occupations, suggesting this margin is quite important. Moreover, our finding that upskilling is concentrated within routine-cognitive occupations and is accompanied by relative wage growth implies that RBTC occurs both within and across occupations. This result helps to clarify work by Beaudry, Green, and Sand (2014, 2016) and others documenting the "great reversal" in demand for cognitive skill. They show that since 2000, cognitive occupations have seen no gains in employment or wages, and that college graduates have become more likely to work in routine occupations than previously. They argue that a decrease in demand for cognitive occupations drove college graduates to take jobs lower in the occupational distribution, squeezing out the high school graduates who formerly held them. This is something of a puzzle, especially given the common belief that technological change continues and the fact that more-skilled workers still earn a sizable premium in the labor market (Card, Heining, and Kline 2013; Card, Cardoso, and Kline 2016). We hypothesize part of the solution to this puzzle is that cognitive workers are being drawn into (formerly) routine-task occupations as the skill content of these occupations evolves. These changes make the occupations more skilled and therefore likely more desirable than before, although probably still not as desirable as traditional high-skilled jobs.[5]

Third, we contribute to a growing literature exploiting data on vacancy postings. Although several studies have used aggregate vacancy data, and even vacancy microdata, from the Bureau of Labor Statistics' Job Openings and Labor Market Turnover (JOLTS) survey (Davis, Faberman, and Haltiwanger 2012, 2013), these data contain little information on the characteristics of a given vacancy or the firm that is posting it. Fewer studies have used vacancy data that contain information on the occupation or specific requirements of the job posted, and these have generally used narrow slices of the data (Rothwell 2014), or data that are limited to one vacancy source (Kuhn and Shen 2013; Marinescu 2017). To our knowledge, we

[4] Additionally, Nickell (1996) provides evidence that increased competition is associated with faster total factor productivity growth; Syverson (2004a, b) shows that productivity is higher in industries and geographies with greater substitutability of products across firms; and Bernard, Redding, and Schott (2011) show firms shift toward higher productivity products upon the liberalization of firm trade. Other examples are cited in each of these papers.

[5] Our analyses, however, do not explain why employment and wages have not grown in high-skill occupations. Deming (2017) proposes a compelling hypothesis that a rising importance of social skills, especially in conjunction with cognitive skills, can help account for this fact.

are the first study to use data based on a near-universe of online job postings that covers every metropolitan area in the United States. Online job vacancies represent but one slice of the labor market, and, by their nature, will overrepresent growing firms (Davis, Faberman, and Haltiwanger 2013). Nonetheless, we show that linking vacancies to data on employment, wages, and capital investments, the last at the firm level, presents consistent evidence on how labor markets changed following the Great Recession.

We demonstrate that during the Great Recession firms changed not only whom they would hire in the recovery, but how they would produce. Instead of occurring gradually, with relatively few workers needing to be reallocated at any given time, we find support that changes in demand for skill were episodic, resulting in a swath of displaced workers whose skills were suddenly rendered obsolete as firms ratcheted up their requirements. The need to reallocate workers on such a large scale may help drive jobless recoveries. It also has distributional consequences, given that low-skill workers are well known to suffer worse employment and wage consequences in recessions.[6] Finally, this type of episodic reallocation likely plays a role in the well-noted and marked decline in male employment-to-population ratios over the past 25 years, especially since these declines have been stair-step around recessions (Moffitt 2012).[7] The evidence provided in this paper is thus integral for understanding worker reallocation, and can help inform policymakers about the optimal mix during a downturn of worker retraining and subsidizing job search through unemployment insurance.

The remainder of this paper proceeds as follows. Section I introduces the data, while Section II summarizes our methodology. Section III presents new facts on changes in skill requirements as a function of local labor market conditions. Section IV investigates how these changes are linked to capital investments. Section V examines cross-occupation heterogeneity in response to local labor market shocks on skill requirements, employment, and wages, with a particular focus on routine occupations. Section VI concludes.

I. Data

Our data come from a unique source: microdata from nearly 100 million electronic job postings in the United States that span the Great Recession (between 2007 and 2015). These job postings were collected and assembled by Burning Glass Technologies, an employment analytics and labor market information firm. In this section, we describe the data and our particular sample construction. We provide a detailed examination of the sample's characteristics and representativeness in online Appendix A.

[6] See von Wachter and Handwerker (2008); Hoynes, Miller, and Schaller (2012); and Forsythe (2016).

[7] Supporting the notion that episodic restructuring drives stair-step declines in male employment, Foote and Ryan (2014) point out that middle-skill workers, the most vulnerable to RBTC, are most at risk of leaving the labor force when unemployed.

A. *Burning Glass Overview*

Burning Glass Technologies—henceforth, BG or Burning Glass—examines some 40,000 online job boards and company websites to aggregate the job postings, parse and deduplicate them into a systematic, machine-readable form, and create labor market analytic products. Thanks to the breadth of this coverage, BG believes the resulting database captures a near-universe of jobs that were posted online. Through a special agreement, we obtained these posting-level data for the years 2007 and from 2010 through 2015, covering every MSA in the United States.[8]

The two key advantages of our data are its breadth and detail. The broad coverage of the database presents a substantial strength over datasets based on a single vacancy source, such as CareerBuilder.com. While the JOLTS asks a nationally representative sample of employers about vacancies they wish to fill in the near term, it is typically available only at aggregated levels, and contains relatively little information about the characteristics of vacancies. In contrast, the BG data contain some 70 possible standardized fields for each vacancy. We exploit detailed information on occupation, geography, skill requirements, and firm identifiers. The codified skills include stated education and experience requirements, as well as thousands of specific skills standardized from open text in each job posting.[9] The data thus allow for analysis of a key, but largely unexplored, margin of firm demand: skill requirements within occupation.[10] Moreover, they allow for a firm-level analysis, which, as we show below, is key to disentangling mechanisms for upskilling.

However, the richness of the BG data comes with a few shortcomings. Notably, the database covers only vacancies posted on the internet. First, Davis, Faberman, and Haltiwanger (2013) show that the distribution of vacancies in JOLTS overrepresents growing firms. Although roughly two-thirds of hiring is replacement hiring (Lazear and Spletzer 2012), vacancies in general will be somewhat skewed toward certain areas of the economy. Second, even though vacancies for available jobs have increasingly appeared online instead of in traditional sources, such as newspapers, one may worry that the types of jobs posted online are not representative of all openings. In online Appendix A, we provide a detailed description of the industry-occupation mix of vacancies in BG relative to other sources (JOLTS, the Current Population Survey, and Occupational Employment Statistics), an analysis

[8] Our dataset was provided in February 2016. Although BG's algorithms for removing duplicates and coding ad characteristics change over time, each iteration is applied to all postings in the data. The database unfortunately lacks postings from 2008 and 2009. These years would be useful for completeness and for understanding the precise timing over which skill requirements changed; however, since hiring volume fell by one-third in 2008 and did not begin to recover until 2010 (per JOLTS), and our focus is on longer-term changes in hiring demand, additional data for the recession years are not integral for this paper. We also have data on jobs posted in Micropolitan Statistical Areas, which we do not use for lack of some of the labor market indicators in these areas, and substantial noise in the ones that are available. They represent 5.6 percent of all posted ads.

[9] For example, an ad might ask for a worker who is bilingual or who can organize and manage a team. BG cleans and codes these and other skills into a taxonomy of thousands of unique, but standardized requirements. Beginning with a set of predefined possible skills, BG searches text in an ad for an indication that the skill is required. For example, for team work, they search for the key words "team work" but also look for variations such as "ability to work as a team."

[10] Other private-sector firms, such as Wanted Analytics, used by the Conference Board's Help-Wanted Online Index, also offer disaggregated data, but not skill requirements. State vacancy surveys, conducted by a limited number of states, sometimes collect certain skill requirements, but cover only a few geographic areas and are generally not comparable across states (Carnevale, Jayasundera, and Repnikov 2014; Rothwell 2014).

of how it has changed over our sample period, and various validity checks conducted on the data both by us and by other researchers. To briefly summarize, although BG postings are disproportionately concentrated in occupations and industries that typically require greater skill, the distributions are relatively stable across time, and the aggregate and industry trends in the quantity of vacancies track other sources reasonably closely.

Another downside of the BG data is that vacancies represent just one margin by which a firm may adjust labor inputs: through stated, but not necessarily realized, demand. For a complete picture, one would also like to see hires, separations, wages, and other measures (e.g., incumbent worker training, recruitment intensity (Davis, Faberman, and Haltiwanger 2013)). Thus, we also provide corroborating evidence on some of these margins using supplemental datasets, as described later.

We restrict our main BG sample to ads with non-missing employers that posted at least 10 ads over the sample period of 2007 and 2010–2015. Employer name is missing in 40 percent of postings, primarily from those listed on recruiting websites that typically do not reveal the employer.[11] Many of our analyses exploit firm-level information to distinguish among possible mechanisms for upskilling. We therefore choose to focus our entire analysis on the consistent sample of ads with non-missing firms, with a sufficient number of observations per firm to estimate firm-level characteristics. However, we have performed analyses not requiring firm-level information on the full dataset and obtain very similar results. Moreover, we have confirmed that the probability of satisfying this sample criterion (having a valid firm identifier) does not vary over the business cycle (see online Appendix A.8). Thus, our sample restriction should not confound the estimated relationship between local labor market conditions and the skill requirements of postings.

B. *Skill Requirements in Burning Glass*

In our analyses, we exploit four categories of skill requirements: stated education and experience requirements, stated demand for skills that we classify as "cognitive," and stated demand for computer skills. We choose these skill requirements for two reasons. First, they represent a broad swath of human capital measures in which both employers and economists have interest. Second, they reflect what the economics discipline has learned about technological change over the past 20 years (Autor, Levy, and Murnane 2003; Brynjolfsson and McAfee 2011). In particular, the RBTC literature emphasizes that new information technology or cheap overseas labor substitute for routine, algorithmic, middle-skill tasks. These new technologies are in turn complementary with high-skill cognitive, abstract tasks.[12] High-skilled workers favored by RBTC may be required to work with computers and perform a

[11] When name is available, Burning Glass uses a proprietary algorithm to group name variants into a standard set: for example, "Bausch and Lomb," "Bausch Lomb," and "Bausch & Lomb" would be grouped together. We also perform some additional cleaning on firm name, removing any remaining punctuation, spaces, and a few problematic words, such as "Incorporated" or "Inc." The 10-ad restriction drops about 4 percent of job ads that list a firm name. However, employer names with very few ads are likely to be miscoded (for example, capturing a fragment of the city name).

[12] This literature finds also that RBTC may indirectly affect low-skill, manual tasks (Autor and Dorn 2013). A downside of the BG sample is that low-skill jobs are underrepresented. We thus focus our analysis on the degree to which employers shift demand from medium- toward high-skill tasks and workers.

more versatile set of functions. Indeed, the non-algorithmic tasks that complement routine-task performing machines or overseas labor involve more complexity, problem solving, and analytical skills, and the ability to determine which tasks need to be performed at a given moment.

In accord with human capital theory, we believe more-educated workers or those with greater experience on the job will be better able to perform these functions.[13] In online Appendix A.3, to cross-validate the data, we show that education requirements strongly correlate with average education levels of employed workers at the MSA and occupation levels.

We categorize cognitive and computer skill requirements based on the open text fields for skills. We designate an ad as requiring computer skills if it contains the key word "computer" or it is categorized as software by BG.[14] We define cognitive skill requirements based on a set of key words chosen deliberately to match the non-routine analytical job tasks used in Autor, Levy, and Murnane (2003) and subsequently used by the majority of papers studying RBTC and polarization. We also ensure that the presence of these key words correlates with external measures of cognitive skill at the occupation level.[15]

This set of skills (education, experience, cognitive, and computer) aligns well with our priors on how jobs change with the availability of computers (Brynjolfsson and McAfee 2011). For example, a sales person who previously devoted most of his or her energy to client relations may now be required to use data analytics to better target packages to clients. This salesperson now needs computer and analytical skills, and some experience in the field may help in mapping data recommendations to practice. Similarly, thanks to machine vision technology, a quality control operator no longer need spend his or her time measuring and identifying the shapes of produced goods, but instead can be diverted to other tasks such as troubleshooting and making judgment calls in design optimization. This set of tasks requires higher cognitive function and intuition that can be gained by experience.[16]

Table 1 summarizes data for the primary regression sample.[17] In 2007, 34 percent of the weighted ads list any education requirement (column 1, row 1). Among ads with an education requirement, one-half (17 percent of all ads) specify minimum education of a bachelor's degree, another one-quarter ask for a high school diploma,

[13] In the raw data, there are two fields each for education and experience requirements: a minimum level (degree or years of experience) and a preferred level. Postings that do not list an education or experience requirement have these fields set to missing. We use the fields for the minimum levels to generate variables for the presence of an education or experience requirement as well as the number of years of education or experience required; the minimum is much more commonly specified than the preferred, and it is always available when a preferred level is listed.

[14] BG includes common software (e.g., Excel, PowerPoint, AutoCAD), as well as less common software and languages (e.g., Java, SQL, Python).

[15] Specifically, an ad is categorized as requesting a cognitive skill if any listed skills include at least one of the following phrases or fragments: "research," "analy," "decision," "solving," "math," "statistic," or "thinking." The fraction of ads at the occupation level that contain each of these skills is strongly correlated with an O*NET measure developed by Deming (2017) meant to categorize cognitive occupations. We obtain this measure from Deming and Kahn (2018), who categorize a wide range of key words found in the BG job ads into 10 general skills, including cognitive.

[16] It has been suggested by Deming (2017) and others that technology complements workers with interpersonal skills, since machines are still poor at reading and inferring human emotion. We have also analyzed changes in demand for a composite "social" skill requirement and obtained results very similar to those presented here on cognitive and computer skills.

[17] In the top two panels, observations are weighted as they are in our regression analyses: we give equal weight to ads within an MSA-year, but upweight larger MSAs, based on the size of the labor force in 2006.

Table 1—Summary Statistics

	Mean (SD)		
	2007	2010–2015	Change
Panel A. Ad characteristics			
Education requirements			
Any	0.34	0.57	0.23
	(0.06)	(0.05)	
HS	0.09	0.20	0.10
	(0.03)	(0.05)	
BA	0.17	0.27	0.10
	(0.05)	(0.08)	
>BA	0.03	0.05	0.02
	(0.01)	(0.01)	
Years, conditional on any	14.84	14.67	−0.18
	(0.40)	(0.44)	
Experience requirements			
Any	0.32	0.52	0.20
	(0.06)	(0.07)	
0–3	0.13	0.24	0.11
	(0.03)	(0.03)	
3–5	0.14	0.21	0.07
	(0.03)	(0.04)	
>5	0.05	0.08	0.03
	(0.02)	(0.04)	
Years, conditional on any	3.52	3.34	−0.18
	(0.47)	(0.54)	
Skill requirements			
Any stated skills	0.73	0.91	0.18
	(0.05)	(0.04)	
Cognitive, conditional on any	0.22	0.34	0.11
	(0.05)	(0.06)	
Computer, conditional on any	0.28	0.39	0.11
	(0.06)	(0.08)	
Panel B. Share of ads in 2010–2015 matching to 2007 and to other datasets			
Missing ACS match	0.08		
Continuing firm	0.65		
In Harte-Hanks, among continuing	0.78		
In Compustat, among continuing	0.40		
	Mean	Min	Max
Panel C. Cell counts			
Number MSAs	381		
Posts per MSA-year	21,779	132	1,231,417
Number occupations (four-digit)	108		
Posts per occupation-MSA-year	228	1	194,558
Number firms	170,809		
Posts per Firm-MSA-year	13	1	16,413

Notes: Burning Glass data 2007 and 2010–2015. All changes are statistically significant at the 1 percent level. Sample is restricted to ads with non-missing firms that posted at least ten ads over our sample period. In the top panel, observations are weighted by the size of the MSA labor force in 2006. Missing ACS match is the share of weighted observations to MSAs that cannot be matched to the American Community Survey (weighted by the MSA labor force). Continuing firms are the fraction of 2010–2015 observations posted by a firm that also posted in 2007. In Harte Hanks (Compustat) among continuing firms are the share of weighted observations that post to a firm that can be matched to Harte Hanks (Compustat). All three statistics are calculated weighting by the firm's ad share in the MSA-year times the size of the MSA labor force in 2006.

and the remainder are roughly evenly split between associate degrees (not shown), master's degrees, and professional degrees or PhDs. Converting the degrees to their modal equivalent years of schooling, the average education requirement, conditional on one being specified, is nearly 15 years.

The second column shows skill requirements averaged over the period 2010–2015. The third column shows the within-MSA change in skill requirements across the two sample periods. The share of ads specifying an education requirement increased by 23 percentage points (ppts), on average. This is roughly evenly split across ads requiring high school and ads requiring college; because the proportional increase is slightly larger for high school, the overall (conditional) years of schooling falls slightly. All differences in means are statistically significant at the 1 percent level.

Experience requirements follow a very similar pattern to education requirements. In 2007, almost one-third of ads specify some amount of experience in the field. Among ads with a requirement, the vast majority ask for less than five years, with much of the remainder asking for between 5 and 10 years. Conditional on posting an experience requirement, the average ad asks for 3.5 years. In the later time period, the propensity to specify an experience requirement increases by 20 ppts. These increases are again concentrated in the lower categories, so that the average, conditional on specifying any requirement, falls by about one-fifth of a year.

Finally, in 2007, 73 percent of weighted ads specify at least one specific, text-based skill requirement. Among these, 22 percent specify a cognitive skill requirement, and 28 percent have a computer requirement. In 2010–2015, 91 percent of ads have at least one text-based skill requirement, and the shares specifying cognitive skills or computer skills increase to roughly one-third and two-fifths, respectively. In regression analyses, we use the probability of posting a cognitive or computer skill requirement, *conditional* on posting a specific text-based skill, as dependent variables, rather than the unconditional probabilities, which might instead pick up a tendency for ads to become more verbose as posting costs decline.

These increases in stated skill demand could be driven by the national recession that took place between 2007 and the 2010–2015 period. However, they could also be driven by a variety of other factors, such as changing composition of firms posting ads online or preexisting national trends. Because of these issues and the relatively short panel we have to work with, our regression analyses always control for year dummies. We therefore fully absorb the overall change in skill requirements illustrated in Table 1. Instead, we identify differences in the change in skill requirements across metro areas as a function of how they weathered the Great Recession.

The bottom panel of Table 1 provides an idea of our sample coverage. We have a balanced panel of 381 MSAs, which contain an (unweighted) average of 21,779 posts per MSA-year. When we disaggregate to the four-digit occupation level, we have 108 occupations represented, with an average of 228 posts in each occupation-MSA-year.[18] Finally, our data contain roughly 171,000 unique firms, which translate into an average of 14 posts in each firm-MSA-year.

[18] Though occupation is available in the BG data at the six-digit Standard Occupation Classification (SOC) level, we restrict our attention to comparisons across and within four-digit SOC codes, which provide more ads per occupation-MSA-year cell and ensure a balanced panel of occupation-MSAs across years in nearly all cases. Virtually all ads posted in the 2010–2015 period are in occupation-MSAs that also posted in 2007; for within-occupation analyses, we drop the 0.36 percent of ads that cannot be matched.

II. Methodology

Our goal is to understand how the Great Recession affected the demand for skill. Because we have only a short panel and need to worry about concurrent trends that may have affected online job ads (e.g., utilization, prices, preexisting national trends in upskilling), we exploit cross-sectional geographic variation in the severity of the Great Recession. Our general approach is to examine temporal changes in skill requirements as a function of an MSA-level employment shock generated by the Great Recession.

Our initial regression specification is shown in equation (1). The term $outcome_{gmt}$ is any of several different measures associated with changes in labor skill demand (and eventually changes in other production inputs, as discussed later) in MSA m, year t, and sometimes in subgroup g (for example, occupation or firm). The left-hand side is the difference in the outcome variable between 2007 and year t. The regression sample thus includes each post-recession year $t \in [2010, 2015]$. Finally, $shock_m$ is a measure of the local employment shock generated by the Great Recession, I^t are year dummies, *controls* are additional control variables described in more detail below, and ε_{gmt} is an error term:

$$(1) \quad outcome_{gmt} - outcome_{gm2007} = \alpha_0 + [shock_m \times I^t]\,\alpha_1 + I^t + controls + \varepsilon_{gmt}.$$

The variable $shock_m$ is fixed at the MSA-level for our entire sample period; we describe its construction in detail below. Through an exhaustive set of $shock_m$-year interactions, the regression estimates the impact of the local employment shock on the *change* in skill requirements (or other outcomes) for a given MSA (and group) between 2007 and a subsequent year. The difference specification implicitly controls for time-invariant factors at the MSA (or group-MSA) level. We use 2007 as the base year in most analyses since this is the only pre-recession year available in BG. Such a specification allows us to empirically investigate the timing and persistence of upskilling in relation to local labor market shocks through the vector of coefficients, α_1. The inclusion of year fixed effects (I^t) means we identify the key coefficients purely off of differences across metro areas in the employment shock, rather than relying on the national shock itself.

We cluster standard errors by MSA to address possible serial correlation within an area. For regressions at the MSA-year level, we weight observations by the size of the MSA's labor force in 2006. This weighting scheme allows us to upweight areas with larger populations, helping with precision, while fixing the weight applied to each MSA-year. The latter ensures that we identify off of the same MSA weighting mix in each year, regardless of any (endogenous) changes in ads posted. When we further disaggregate to the MSA-year-group level, we weight cells by the product of the 2006 MSA labor force and the group's observation share within MSA-year (the observation shares sum to unity), so that more aggregate regressions produce results identical to those using more disaggregated data when the underlying specification is the same.

The key explanatory variable, $shock_m$, is the MSA-specific change in projected annual employment growth between 2006 and 2009, the national peak and trough years surrounding the Great Recession. We project employment growth in an MSA based on its employment shares in three-digit North American Industry Classification System (NAICS) industry codes averaged over 2004 and 2005 and national employment changes at the three-digit industry level. This type of shift-share method is sometimes referred to as a Bartik shock, following the strategy of Bartik (1991).[19]

Specifically, we define projected employment growth, $\Delta \hat{E}_{mt}$ in equation (2), where for K three-digit industries, ϕ is the employment share of industry k in MSA m at time τ (in practice, τ is the average of 2004 and 2005), $\ln E_{kt}$ is the log of national employment in industry k in year t, and $\ln E_{kt-1}$ is the log of national employment in the industry one year prior:[20]

$$(2) \quad \Delta \hat{E}_{mt} = \sum_{k=1}^{K} \phi_{m,k,\tau}(\ln E_{kt} - \ln E_{k,t-1}), \quad shock_m = \Delta \hat{E}_{m2009} - \Delta \hat{E}_{m2006}.$$

We then define $shock_m$ as the change in projected employment growth from peak to trough (2006 to 2009). The calculated values of $shock_m$ range from about -0.12 to -0.04 across MSAs, but to make the coefficients easier to interpret, we renormalize this variable so that a one unit change is equal to the difference between the tenth and ninetieth percentile MSAs, -0.026 log points; a larger value corresponds to a worse economic shock.

We use this Bartik measure, instead of actual employment growth, for two reasons. First, actual employment growth at the MSA level is measured with substantial error, while the Bartik measure allows for more precision. Second, actual employment growth will reflect shocks to labor demand as well as other city-specific shocks, including those to labor supply, which may be problematic.[21] We note that other direct measures of local labor market tightness, such as the local unemployment rate, have similar shortcomings in terms of measurement error or reverse causality; for instance, an unemployment rate may be high precisely *because* a sudden demand shift toward more-skilled labor generates structural mismatch. We examine the robustness of our results to other ways of defining the Bartik shock.

The top left panel of Figure 1 summarizes the relationship between the Bartik employment shock and actual annual (log) employment growth at the MSA level (obtained from the BLS State and Metro Area Employment program). We estimate equation (1), which nets out the actual employment growth rate in 2007 through the differences specification, for 2000–2015, controlling only for year fixed effects. The coefficients, α_1, thus represent difference-in-differences estimates: the change in actual employment growth between a given year t and 2007, for a hard-hit MSA (ninetieth percentile employment shock) relative to a less hard-hit MSA (tenth percentile employment shock).

[19] Some other papers utilizing a form of Bartik shock include Blanchard and Katz (1992), Notowidigdo (2011), and Yagan (2016).

[20] We obtain seasonally adjusted national employment for each three-digit industry-month from the BLS Current Employment Statistics program, and take an unweighted average over months to obtain E_{kt}. We construct ϕ using County Business Patterns data and the algorithm of Isserman and Westervelt (2006) to overcome data suppressions; the resulting county-level statistics are mapped to MSAs using the definitions provided by the Census Bureau and set by the Office of Management and Budget. See http://www.census.gov/population/metro/data/def.html.

[21] For example, MSAs with secular increases in population due to migration flows may experience employment changes that are higher than average but still have a weakening labor market. The Bartik shock addresses this issue.

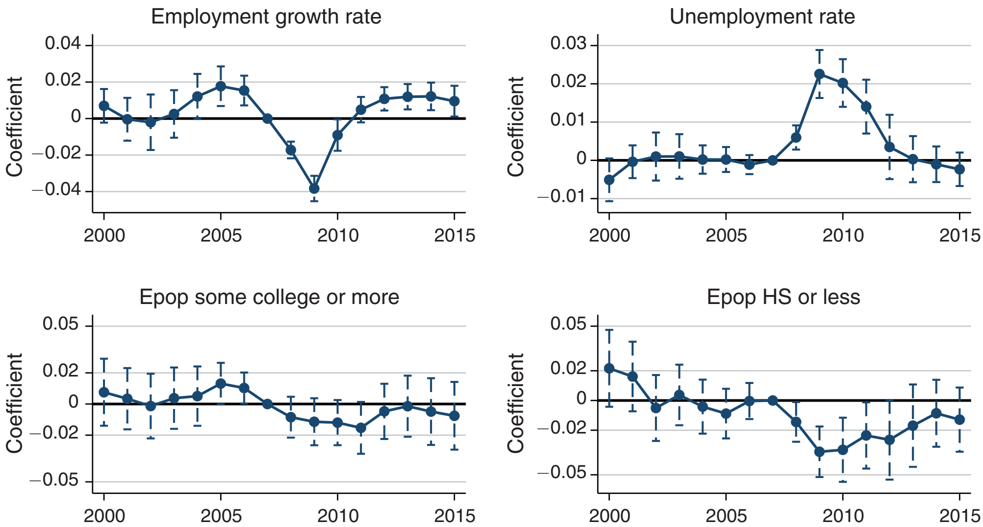


FIGURE 1. LABOR MARKET VARIABLES AND THE MSA-SPECIFIC EMPLOYMENT SHOCK

Notes: 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 percent CI bars. Unemployment and employment growth rates are from the BLS. Employment-to-population ratios (Epops) are author calculations based on the CPS.

We plot the coefficients α_1 and 95 percent confidence-interval bars (results for Figure 1 are also displayed in columns 1–4 of online Appendix Table C1). For example, the point estimate of −0.038 in 2009 (top left panel of Figure 1) indicates that a one-unit change in the Bartik shock is associated with an additional 0.038 log-point drop in employment growth between 2007 and 2009. The difference between 2006 and 2009, which corresponds to our Bartik shock definition, that is associated with a one-unit increase in $shock_m$ is -0.053 $(= -0.038 - 0.015)$. This is roughly double the Bartik 90–10 gap of −0.026 associated with a one unit change of $shock_m$ used in the regression. The actual BLS variables are likely substantially noisier than projected employment growth and also are influenced by other factors, such as supply shocks.

The figure also shows that the shock is episodic, such that employment growth (relative to that in 2007) looks similar across MSAs early in the decade, regardless of the size of the shock they will eventually face in the Great Recession. Hard-hit MSAs peak slightly higher than less hard-hit MSAs in 2005 and 2006, then experience a sharp dip in employment growth from 2007–2010, followed by a recovery.[22]

The Bartik shock measure is also highly correlated with movement in the unemployment rate (obtained from the BLS Local Area Unemployment Statistics program). The top-right panel of Figure 1 shows that a hard-hit MSA experiences an additional 2 percentage point increase in the unemployment rate from 2007 to 2009, relative to a less hard-hit MSA. Again, areas look very similar in the period before the recession, and converge a few years after the recession ends.

[22] We use the 2006-2009 differential because these are the peak and trough years of our Bartik shock. As can be seen in Figure 1, actual employment growth in hard-hit MSAs peaks slightly earlier, in 2005, but remains almost at the same magnitude in 2006.

Our primary regressions of interest involve changes in skill requirements within MSA using data that begin in 2007. Although the first-difference specification nets out differences across MSAs in the level of posted skill requirements, we cannot control for (or observe) any preexisting trends within MSAs in skill demand. Identification may be threatened if, for example, preexisting trends in upskilling were more prevalent in MSAs with industry mixes that would make them more or less susceptible to the demand shock.

The bottom panels of Figure 1 help speak to this concern by examining employment-to-population ratios (epop) by education group. We calculate these variables by MSA using CPS microdata, so they are naturally a bit noisier than the variables in the top panel (see online Appendix A.7 for details about this sample construction). The epops for workers with at least some college (bottom left) and for workers with a high school diploma or less (bottom right) are fairly similar across MSAs before the Great Recession. This is shown in the figure by point estimates that are small in magnitude and generally statistically indistinguishable from zero prior to 2007. As with employment growth, the college epop does peak slightly higher in 2005 and 2006 for MSAs that will experience a worse shock; additionally, the epop for less-educated workers fared modestly better in these MSAs in 2000. However, differences are small and do not appear to be systematic trends.

After 2007, both education groups experience relative drops in epops, though that for college workers is shallow and recovers quickly. The decline in epop for less-educated workers is both more severe and more sluggish to recover, and a gap of roughly 1 ppt still remains in 2015.[23] This lack of convergence may suggest that harder-hit areas had not fully recovered from the Great Recession by 2015. We revisit this lack of complete recovery below when we discuss our proposed mechanism.

To alleviate remaining concerns about differential pre-trends, we control, where specified, for a wide range of MSA characteristics (including demographics, educational attainment, and economic indicators) obtained from the American Community Survey (ACS), averaging years 2005 and 2006.[24] These controls help adjust for differences across MSAs in their preexisting tendency to upskill, to the extent that such a tendency is correlated with the skill distribution of the population or the health of its economy before the Great Recession.

To summarize, we find that our constructed Bartik employment shock is episodic: although it is highly correlated with changes in employment growth rates and the unemployment rate during the Great Recession, the shock is not correlated with

[23] This finding is consistent with Yagan (2016), who uses IRS tax data to show that while unemployment rates had converged across US commuting zones following the Great Recession, employment probabilities had not, holding constant a rich set of worker characteristics.

[24] We chose years just prior to the Great Recession that allow for MSA identification (prior to 2005, the ACS lacks substate identifiers). Specifically, we include the share of the population that is female, black, Hispanic, Asian, married, migrated in the last year, is a high school dropout, 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, and is age 50–64. We also control for the employment-to-population ratio and the average weekly wage of full-time workers. We can match all but 8 percent of weighted ads to the ACS (see the middle panel of Table 1), with unmatched ads consisting of small MSAs not identifiable in the ACS. In such cases, we set the ACS controls to zero and include an indicator for not matching. In online Appendix B.2, we also include specifications that add controls for *changes* since 2000 in these variables.

these labor market fundamentals before the Great Recession or several years into the recovery. As we cannot observe skill requirements before 2007, this is reassuring: the lack of pre-trends in the labor market variables in Figure 1, and for others described below, makes it less likely that areas were differentially trending in skill demand before 2007. Below, we explore the relationship between the shock measure and a range of additional labor market variables.

III. Skill Requirements and Local Employment Conditions

A. *Main Results*

Figure 2 summarizes regression results from equation (1) for our four main dependent variables: the change in the share of ads posting any education requirement, any experience requirement, any cognitive requirement, and any computer requirement (results are also displayed in columns 5–8 of online Appendix Table C1). The figures plot the estimated impact of the Bartik shock on the change in skill requirements for each year, relative to 2007 (coefficients α_1), as well as 95 percent confidence intervals. We use our preferred specification, which includes controls for MSA characteristics and year fixed effects.

Beginning with the top left panel, we find that, relative to 2007 levels, the probability of specifying any education requirement increases by 5.4 ppts in 2010 for an MSA experiencing a large employment shock (ninetieth percentile) compared to an MSA experiencing a small shock (tenth percentile). This difference-in-differences estimate implies an increase of 16 percent of the average requirement in 2007 and is significant at the 1 percent level. The effect persists at fairly similar magnitudes and significance levels for subsequent years, with a small dip in 2012. In 2015, we estimate that the probability of posting an education requirement is still 4.1 ppts larger than it was in 2007 for a hard-hit MSA, compared to a less hard-hit one. That is, 76 percent of the initial upskilling effect in 2010 remains five years later. Estimates in each year except 2012 are significant at the 1 percent level.

The remaining panels of Figure 2 exhibit remarkably similar patterns in both magnitudes and statistical significance. The probability of listing an experience requirement increases by 5.0 ppts (16 percent) between 2007 and 2010, and 85 percent of this increase remains in 2015. The probability of listing a cognitive requirement increases by 2.0 percentage points (12 percent), and this gap widens slightly by 2015. Finally, the probability of listing a computer skill requirement also increases by roughly 2 ppts and remains elevated through 2015.

These patterns are in stark contrast to the labor market variables in Figure 1. For employment growth, the unemployment rate, and the epop for college workers, hard-hit MSAs experience a severe impact of the Great Recession that fully recovers within our sample time frame. For illustration, compare Detroit and Pittsburgh. The former, a hard-hit MSA, experienced a shock at about the ninetieth percentile, while the latter was at roughly the tenth percentile. Both MSAs had similar skill requirements in 2007; for example, in both areas about one-third of ads had an education requirement. By 2010, skill requirements increased in both MSAs, but Detroit's (actual, not predicted) increase was nearly 10 ppts larger for education and experience requirements and 2–4 ppts larger for cognitive and computer skill

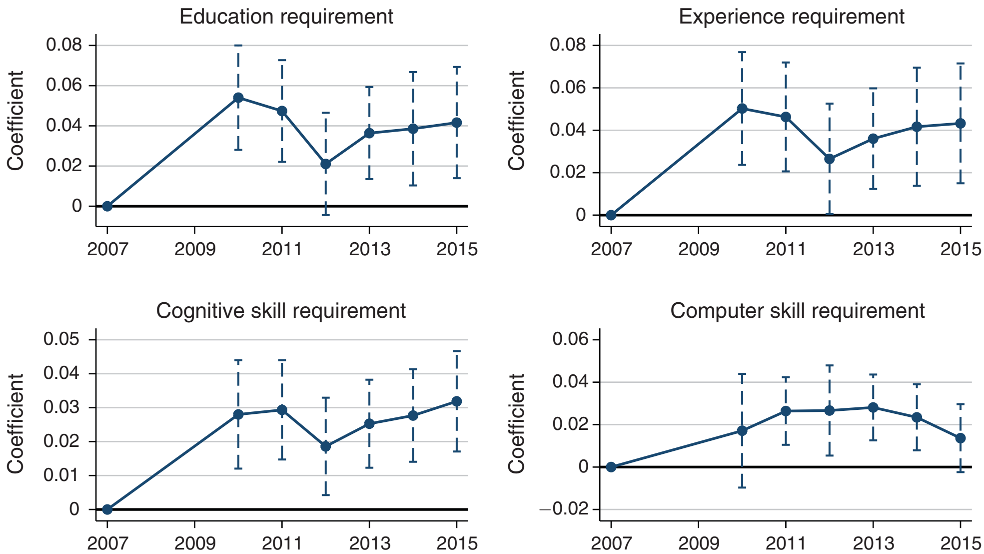


Figure 2. Skill Requirements and the MSA-Specific Employment Shock

Notes: We regress the MSA-level 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 percent confidence intervals.

requirements. While unemployment rates had converged back to pre-recession levels in both MSAs, Detroit's elevated skill requirements persisted through 2015.

Figure 2 demonstrates that the case of Detroit and Pittsburgh is not isolated but systematic. In terms of their skill requirements, MSAs that looked similar before the Great Recession look quite different from each other in 2015, several years after the Great Recession ended.

To better understand the mechanisms underlying Figure 2, Table 2 provides regression results for within-occupation changes in skill requirements. In general, the distribution of postings across high- and low-skilled jobs may vary for a variety of reasons. For example, differential job survival, use of word-of-mouth in recruiting, or time-to-fill across skill groups might generate patterns observed in Figure 2, especially early in the recovery. However, we find that the primary driver of these patterns is increased skill requirements within similar types of jobs.

Each column of Table 2 summarizes a separate regression of equation (1), at the occupation-MSA-year level, including MSA characteristics and year fixed effects. The results show significant upskilling effects of a magnitude comparable to the overall MSA-level effects. For example, within occupation, the propensity to post an education requirement increases by 5.3 ppts in a hard-hit MSA, relative to a less hard-hit MSA, between 2007 and 2010. Although there is a temporary dip in 2012, at least three-quarters of this effect persists from 2013 through 2015. Similar patterns obtain for the remaining skill requirements. Indeed, these within-occupation increases in skill requirements completely account for the MSA-level upskilling effects found in Figure 2; our upskilling results are not driven at all by changes in the occupation mix of postings. (This does not preclude variation in effects across

TABLE 2—WITHIN-OCCUPATION CHANGES IN SKILL REQUIREMENTS

	Education (1)	Experience (2)	Cognitive (3)	Computer (4)
Shock × 2010	0.0526	0.0490	0.0275	0.0203
	(0.0135)	(0.0134)	(0.00726)	(0.00859)
Shock × 2011	0.0475	0.0443	0.0281	0.0243
	(0.0131)	(0.0134)	(0.00731)	(0.00716)
Shock × 2012	0.0233	0.0253	0.0186	0.0207
	(0.0128)	(0.0136)	(0.00693)	(0.00848)
Shock × 2013	0.0400	0.0363	0.0253	0.0252
	(0.0120)	(0.0122)	(0.00642)	(0.00664)
Shock × 2014	0.0429	0.0436	0.0265	0.0227
	(0.0143)	(0.0140)	(0.00657)	(0.00679)
Shock × 2015	0.0488	0.0468	0.0300	0.0134
	(0.0143)	(0.0142)	(0.00730)	(0.00807)
Number Occ-MSA-Year Cells	193,086	193,086	178,176	178,176
R^2	0.044	0.069	0.040	0.034

Notes: Regressions are estimated at the MSA-occupation (four-digit SOC)-year level using BG data from 2010–2015 (see equation (1)). The dependent variable is the MSA-occupation 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 occupation's ad share in the MSA-year. 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. Columns 3 and 4 restrict to the sample of ads that have any specific skill requirements and therefore estimate the change in the probability of listing a cognitive or computer skill, conditional on having any requirement.

occupations, and we examine such heterogeneity, with a particular focus on routine jobs, in Section V.)

In order to understand within-occupation skill demand changes along the intensive margin, we also explore the effect of the shock on specific levels of education and experience requirements in online Appendix B.1. To summarize, we find effects throughout the distribution along expected channels: low-skilled jobs become more likely to ask for a high school diploma, higher-skilled jobs become more likely to ask for a college degree, and experience requirement increases are concentrated especially within the 1–5 year range.

One hypothesis for these results is that firms may become pickier when labor, and especially skilled labor, becomes more plentiful.[25] Then elevated skill requirements might reflect opportunistic behavior on the part of firms that cannot ordinarily attract (or afford) more-skilled workers in a tight market.[26] This hypothesis would be compelling if the market for skilled workers remained more slack toward the end of our sample period, even while some labor market indicators had recovered. However, our results are similar when we include additional controls for local labor

[25] Or, as in Menzio and Shi (2011), firms require a higher-quality match in a recession because of the negative productivity shock.

[26] Evidence shows that in downturns workers are more likely to take worse jobs, relative to their skills, but it is unclear whether this is driven by changes in firm recruitment strategy and/or worker search behavior (Devereux 2002; Kahn 2010; Oreopoulos, von Wachter, and Heisz 2012; Altonji, Kahn, and Speer 2016).

market variables by skill level, such as education-specific MSA-level unemployment rates, quit rates, and employment-to-population ratios. These controls account for changes in the supply of skilled labor due to, for example, differential quit behavior or changes in educational attainment brought on by the Great Recession or over the preceding decade (Charles, Hurst, and Notowidigdo 2015). We conclude that opportunistic upskilling cannot be the primary driver of our results.[27]

Online Appendix B.2 discusses these and other robustness checks in detail, which are summarized in online Appendix Tables B1–B4. Our results broadly hold up to additional controls, different samples, variants of the Bartik shock, and different weights. For example, our estimates are robust to controls for occupation fixed effects and occupation-specific time trends, which allow occupations to systematically differ in their change in skill requirements from 2007, as well as in the slope of the change, across all MSAs. These could be important if some occupations are both more likely to upskill or accelerate upskilling because of preexisting trends and are disproportionately located in hard-hit MSAs.

We have also explored heterogeneity within and across industry. We show in online Appendix Table B5 that our results hold up to industry fixed effects and time trends, which is important in light of our identifying variation: industry composition in an MSA before the Great Recession. Our identification would be threatened by independent technology shocks concurrent to industries that experienced worse employment shocks or by systematic measurement error in industry shares (which could lead to spurious correlations in the shock across MSAs). The fact that our results obtain even within industry alleviates these simultaneity and measurement concerns. We further show in online Appendix Figure B3 that the upskilling effects tend to be concentrated in industries with locally consumed products, as would be expected given their greater sensitivity to local demand shocks.

Finally, one may be concerned about changes in the use of online job ads over our sample period. Rising familiarity with the internet, falling costs of posting jobs, increasing labor market tightness in the later period, and other factors may have brought more firms online to search for labor. The within-occupation and -industry results partially address the role that compositional changes in the use of online job ads may have on our results by restricting comparisons to similar types of jobs. However, they may not adequately control for heterogeneity across firms in, say, changes to their recruiting strategies or hiring needs. Such variations may be particularly pronounced during and after a recession.

In online Appendix B.3 we conduct a formal decomposition exercise to apportion upskilling effects as a function of within- and between-firm responses. Indeed, we do find a large role for substitution between firms that stopped posting after 2007 and firms that began posting in 2010. As the latter post for higher skill requirements on average than the former, this substitution can account for nearly one-half of the

[27] In a pair of related papers and concurrent with our analysis, Sasser Modestino, Shoag, and Ballance (2016a, b), using a version of our dataset, find evidence of upskilling in harder-hit US counties after the Great Recession and subsequent downskilling as markets improved, and argue that this pattern is driven entirely by firms opportunistically seeking more-skilled workers in a slack labor market. We disagree with this conclusion, which relies heavily on the small downward blip in 2012, seen also in our Figure 2, rather than the more careful picture generated by using all available data. In our paper, we also examine heterogeneity within and across firms and occupations and other margins of adjustment, such as capital, employment, and wages. This richer analysis implies more fundamental changes in production inputs and longer-lasting impacts.

full upskilling effect from Figure 2. However, we also find that nearly one-half of the effects can be attributed to changes in skill requirements within firms, with a minimal role for compositional shifts across firms that post before and after the recession. This suggests that our results are not completely driven by the compositional changes mentioned above.

B. *Discussion*

We thus present strong evidence that employers in harder-hit MSAs were differentially induced to increase stated preferences for a range of skills. While most measures of local labor-market strength had converged back to pre-recession levels by 2015, differences in advertised skill demands remained. Furthermore, variation in the availability of skilled labor and compositional changes in the ads observed in our sample period are unlikely to explain the entire effects that we find.

This set of results raises the possibility that harder-hit MSAs differentially experienced a structural change in demand for skill. In particular, the skill requirements we investigate are complementary to routine-biased technologies. Did the Great Recession push an accelerated adoption of such technologies and accompanied hiring of cognitive workers to complement them? This could explain why skill requirements increase even within similar types of jobs. For example, community and social service specialists at a food bank in Washington, DC might be required not only to interact with clients to assist with food security, but may have to understand and use database software and GIS, as well, to better serve them.[28] Simultaneously, in order to better reach and understand online readers, venerable journalistic organizations such as the *New York Times* now hire individuals with science training, not just journalism training, to be chief data officers.[29] It is also consistent with our finding that epops for workers with less education were slow to recover: rapid adoption of new technologies in hard-hit MSAs over this time period may have rendered certain worker skills obsolete, inducing labor force exit (also see Foote and Ryan 2014). Perhaps the epop of educated workers recovered rapidly precisely because of an increased demand for skill spurred by the Great Recession.

Several theoretical mechanisms may have induced firms to restructure. For example, in the classic Schumpeter (1939) cleansing model, this would occur because low-productivity firms shut down in the recession and resources are reallocated to firms with more-modern production technologies (see also Caballero and Hammour 1994, 1996; and Mortensen and Pissarides 1994). Furthermore, this type of episodic restructuring could also occur because firms in harder-hit MSAs experience a greater negative product-demand shock that: (i) lowers the opportunity cost of adjusting production (Hall 2005); (ii) shifts managerial attention from growth to efficiency (Koenders and Rogerson 2005), perhaps due to increased pressure from risk of bankruptcy (as in the canonical principal-agent model (Gibbons and Roberts

[28] See Terrence McCoy, "The Technology That Could Revolutionize the War on Hunger," *The Washington Post*, June 16, 2015 (http://www.washingtonpost.com/local/the-technology-that-could-revolutionize-the-war-on-hunger/2015/06/16/056d9d52-1114-11e5-adec-e82f8395c032_story.html).

[29] See Rebecca Greenfield, "Why the New York Times Hired a Biology Researcher As Its Chief Data Officer," *Fast Company*, February 12, 2014 (https://fastcompany.com/3026162/why-the-new-york-times-hired-a-biology-researcher-as-its-chief-data-sci).

2012)); (iii) alters the costs of making layoffs (Mortensen and Pissarides 1994, Berger 2012);[30] and (iv) changes the incentives for a firm to invest in their workers' human capital (Jaimovich and Siu 2012). We do not feel we have the ability to disentangle these mechanisms or provide strong support for any one model. Instead, we point out that these types of workhorse models in macroeconomics can rationalize the results that we see.

If firms are changing how they produce, and not simply whom they hire, changes to skill demand should persist among the same firms that initially upskilled. Note that the finding of within-firm upskilling, mentioned above, does not necessarily imply this point, as different firms may have upskilled at different times. The Burning Glass data provide an unprecedented glimpse at this margin at a detailed level, and we examine this prediction in Figure 3. Here, we divide firms into (posting-weighted) quartiles based on changes in skill requirements between 2007 and 2010. We then plot the average skill requirements for each quartile over time.[31] Firms began at fairly similar average skill levels in 2007, although this similarity is not imposed by our exercise. By construction there is a sharp contrast across firm quartiles in 2010, with the darker shaded lines representing firms with larger skill increases. Interestingly, and not by construction, these quartiles remain spread apart throughout the remainder of the sample period, and by 2015, firms in the higher quartiles still had substantially higher skill requirements in their *new* ads than firms in the lower quartiles.

This within-firm persistence in upskilling holds up in regression analysis and is substantial. Though not shown, we find that, on average, 60–70 percent of a firm's increase in skill requirements between 2007 and 2010 persists through 2015. Estimates are even larger when we instrument for the initial increase in upskilling with the Bartik shock. It could have been the case that the majority of firms increased skill requirements during the recession and reverted back later in the recovery (for example, in an attempt to opportunistically recruit while markets were slack), with higher skill demand in later years unrelated to the recession and driven by different firms. Instead, we find upskilling persists among the same firms both early and late in the recovery.

Furthermore, our finding that a substitution across old and new firms accounts for some of the upskilling effect could also be consistent with episodic restructuring. Substitution from failing (low-productivity) firms to new (high-productivity) firms is a hallmark prediction of "cleansing" models of recessions (Schumpeter 1939). In our data, we do not observe firm births and deaths, so the Schumpeter angle is difficult to fully assess. However, we can gain some general intuition by comparing firms that post in 2007 but not again (possibly representing firm closures) to firms that begin posting in the later period but not in 2007 (possibly representing firm openings). (We readily acknowledge we are abstracting away from hiring freezes and migration toward online job postings; we view this exercise as

[30] Though not formalized, a sufficiently large negative product-demand shock could make layoffs worthwhile, offsetting any stigma or losses in terms of firm-specific human capital.

[31] We exploit the subsample of firms in our data that post at least five observations in each of 2007 and 2010, comprising 66 percent of weighted observations. Online Appendix A.8 shows that the probability of satisfying this restriction does not vary with the local labor market shock. Quartiles are defined separately for each skill measure, weighting by the firm average number of posts across 2007–2010.

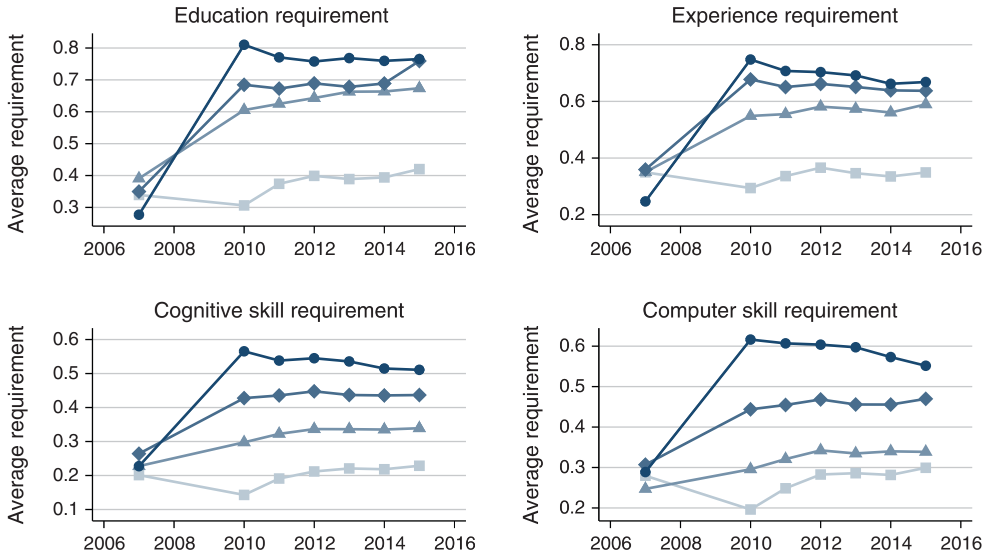


Figure 3. Skill Requirements by Firm, 2007–2010 Change

Notes: Graph plots average BG skill requirement by year and quartile of 2007–2010 firm-level skill change. Circles, diamonds, triangles, and squares indicate skill change quartile from largest to smallest, respectively.

illustrative, not definitive.) We find that "opening" firms indeed have higher skill requirements than "closing" firms, even within occupation, and this is consistent with the Schumpeterian cleansing view (see online Appendix B.3).[32]

The episodic restructuring hypothesis has additional predictions that we can take to the data. First, if changes in skill requirements reflect changes in production inputs, we should see greater investments in capital, and in particular routine-labor replacing technologies, for firms located in harder-hit MSAs. Moreover, the two activities should be linked: the very firms upskilling in their labor demand should be the ones increasing their investments. Second, routine workers whose skills can be substituted with these technologies should experience an immediate contraction in labor demand, as well as relative employment declines in the recovery and beyond. In contrast, the occupations that are complementary to new technology should become more productive, from the increase in both physical and human capital, and thus should exhibit increases in relative wages. We explore these predictions in the next two sections.

IV. Capital

Under episodic restructuring, firms automate routine tasks with technology, which complements skilled labor. If this restructuring is occurring, then firms should also invest in physical capital around the time that they upskill. Information technologies (IT), in particular, have been linked to RBTC (Michaels, Natraj, and Van Reenen

[32] Moreira (2017), who shows that firms that begin in a recession are more productive than those that begin in an expansion, also provides support for the Schumpeterian view.

2014). While investments in capital tend to be procyclical, and production of IT, in particular, has exhibited a secular decline (Byrne, Fernald, and Reinsdorf 2016), these trends could mask substantial heterogeneity.

We first investigate whether harder-hit MSAs are more likely to invest in IT over the Great Recession. To measure IT investment, we use the Ci Technology Database from Harte-Hanks (now known as Aberdeen), a market intelligence firm. The Harte-Hanks database (hereafter, HH) is created from surveys and interviews with high-level IT staff at millions of businesses worldwide each year. They collect data primarily to sell to major IT firms like IBM, Dell, and Cisco.[33]

Following previous work using these data, our primary outcome measure is the number of personal computers (PCs) at a "site" (akin to business establishments). We have this measure consistently available in even years between 2000 and 2014, and we normalize by dividing by site employment in the pre-recession period.[34] We aggregate to the MSA-year level by taking an employment weighted average across sites.

Figure 4 (and column 9 of online Appendix Table C1) summarizes results from equation (1), with the MSA-level change in PCs per employee from 2006 as the outcome. This graph provides evidence that firms located in harder-hit MSAs are more likely to intensify IT investment over the same time period. Our estimates imply that sites in a hard-hit MSA add an average of 1.5 PCs (per each pre-recession employee) between 2006 and 2012, relative to sites in less hard-hit MSAs. Though the confidence intervals are wide, this effect is statistically significant at the 5 percent level in 2008, 2010, and 2012. This differential increase experienced by hard-hit MSAs is substantial, roughly 60 percent more than the average increase across all MSAs (a 0.93 increase in PCs per employee off a base of 0.75).

By 2014 the point estimate has fallen somewhat and is no longer statistically significant, possibly reflecting the beginning of a more gradual catch-up of technology adoption in less hard-hit MSAs. However, the point estimate implies that harder-hit MSAs remain 1 PC per worker ahead of less hard-hit areas, relative to their pre-recession levels.[35]

Furthermore, the estimated coefficients for 2000, 2002, and 2004 are all close to zero and statistically insignificant, implying that MSAs that would be severely affected

[33] We thank Nick Bloom for graciously sharing with us extracts of the HH data as used in Bloom, Draca, and Van Reenen (2016). In that paper, they show that Chinese import penetration increased technological change for exposed firms in Europe. The data have also been used in several other studies. Bloom, Sadun, and Van Reenen (2012), for example, use HH data to show that US multinationals operating in Europe obtain higher productivity from IT investments than non-multinationals; Beaudry and Lewis (2014) show that variation in PC adoption across US space can account for variation in declines in the gender pay gap; and Bresnahan, Brynjolfsson, and Hitt (2002) provide evidence that IT use, work organization that shifts more responsibility to workers, and worker skill are complements in production.

[34] A measure of PCs per employee is desirable to better understand capital intensity (rather than simply growth in size), but as employment may be varying (endogenously) over this time period, we fix the normalization at a period before the Great Recession: the average of each available year among 2002, 2004, and 2006. This normalization means that variation in the outcome is strictly due to the numerator (total PCs), and ensures that greater employment losses in harder-hit MSAs will not mechanically induce a positive association between our PCs measure and the size of the shock. The fixed normalization requires that our sample be restricted to sites that are observed both prior and subsequent to the Great Recession, and this covers 65 percent of employment in HH across our sample years. Online Appendix A.8 shows that meeting this restriction is unrelated to our shock measure.

[35] These relatively large magnitudes are in part driven by long right tails in the distribution of PCs per worker across MSAs and years. To reduce the role of outliers, we have also estimated PC adoption on a sample trimmed of the top and bottom 1 percent of observations; we find qualitatively similar patterns of statistically significant increases in 2008–2012 that gradually decrease to insignificance by 2014, with point estimates that are somewhat smaller in magnitude.

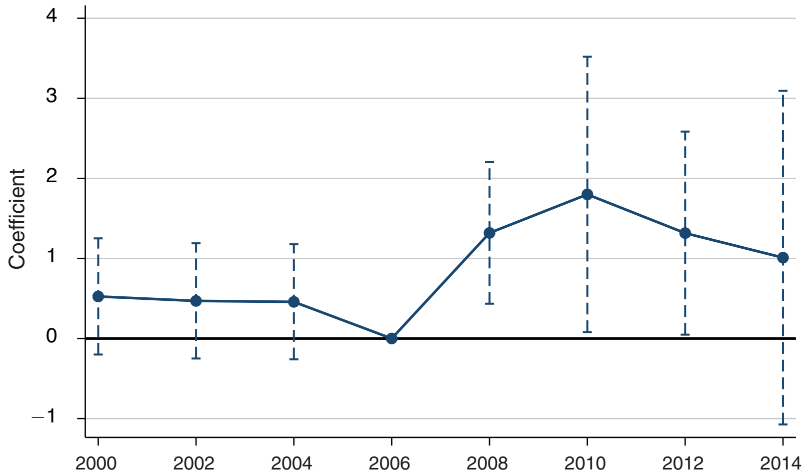


Figure 4. PC Adoption and the MSA-Employment Shock

Notes: We regress the MSA-level change in IT investment from 2006 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, as well as 95 percent confidence intervals. MSA-year IT investment is the employment-weighted average of site-level PCs per pre-recession employment from Harte-Hanks.

had fairly similar IT investment trends before the Great Recession. If anything, there is a slight relative decline in per-worker PCs in these areas between 2000 and 2006, mostly in the last two years of this range, but these estimates are somewhat noisy. Thus, there is no evidence of a capital intensifying trend in harder-hit MSAs before the recession, as the modest relative movement goes in the opposite direction. As with the employment and unemployment rates in Figure 1, it is comforting that the identifying assumptions of the Bartik shock appear to hold. Although we cannot observe skill requirements before 2007, that both employment-to-population ratios by education group *and* IT investments trend similarly across MSAs in the period before the Great Recession should reduce concern about preexisting trends.

In Section IV, we showed not only that advertised job skill requirements increased and persisted in harder-hit MSAs, but that these increases occurred within firms. Since harder-hit MSAs also intensified their IT investments over the same time period, we next explore whether this investment and upskilling are linked at the firm level.

To do so, we link BG job ads at the firm level to two measures of investment from external data sources: PCs per worker from the HH database and capital holdings from Compustat North America by Standard & Poors (Compustat). Compustat is the most complete database of accounting and balance sheet data among publicly traded US firms. Although PCs are a good proxy for overall IT investments, they may miss broader routine-labor replacing investments, such as new machinery, telecom infrastructure, or inventory management systems.[36] Thus, a firm's overall holdings

[36] The Harte-Hanks database contains other measures of IT investment, including servers (for which we generally find results consistent with those from PCs), and specific types of software. Unfortunately, the latter are consistently available only from 2010 onward.

of property, plant, and equipment (hereafter, PPENT) from Compustat is a useful supplement.

We link both datasets to the BG data by firm name. See online Appendix Sections A.4 and A.5 for details on these mergers. In general, we can match more firms to HH than to Compustat, as the former is meant to cover all businesses while the latter is restricted to publicly traded companies. Among employers observed in both 2007 and the later period in BG (which cover 65 percent of postings), we are able to match about 80 percent of postings to firms in HH and 40 percent of postings to firms in Compustat. Online Appendix A.8 shows that the share of ads matching to these samples does not vary with the local employment shock.

We estimate upskilling regressions at the firm-MSA-year level, defined in equation (3). This equation allows for an additional interaction between the shock-by-year variables and the firm-level change in capital investments over the Great Recession ($Capital_f$). Because this is a first-difference specification at the firm-MSA level, we do not include the main effect of $Capital_f$. To reduce measurement error, we define these firm-level changes in capital investment as the difference (PCs) or ratio (PPENT) between the average value in 2010, 2012, and 2014, and the average value in 2002, 2004, and 2006.[37] Formally,

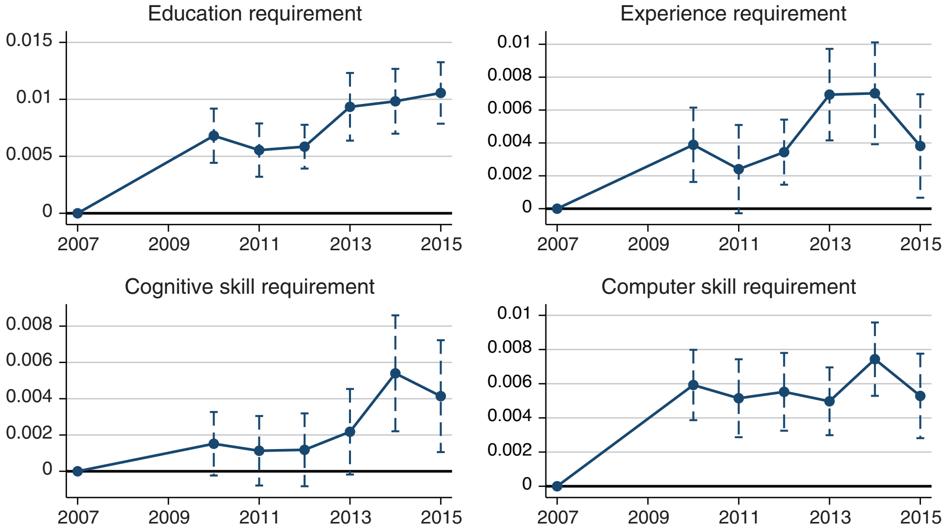
$$(3)\quad outcome_{fmt} - outcome_{fm07}$$
$$= \alpha_0 + [shock_m \times I^t]\,\alpha_1 + [shock_m \times I^t \times Capital_f]\,\alpha_2 + I^t + X_m\beta + \varepsilon_{fmt}.$$

Figure 5 plots the estimated coefficients α_2 (see also online Appendix Table C2). To make them easier to interpret, we plot the fitted effect for the 90–10 percentile differential in firm-level capital change. The ninetieth percentile firm in our sample added roughly two-thirds of a PC per worker at each of its establishments and roughly tripled PPENT. In contrast, the tenth percentile firm lost nearly one-third of a PC per worker and dropped PPENT holdings by about 20 percent.

We find that firms with larger capital investments differentially and persistently increase their skill requirements. For example, the top left panel of Figure 5 (panel A) shows that between 2007 and 2010, holding the employment shock fixed, a firm at the ninetieth percentile of PC investment increased the likelihood of an education requirement in its job postings by 0.7 percentage points more than a firm at the tenth percentile of PC investment. This differential fluctuates somewhat, but persists and grows to about 1.0 percentage point by 2015. This pattern and approximate relative magnitude hold for experience, cognitive skill, and computer skill requirements, with statistically significant differentials in most post-recession years, usually at the 1 percent level. Overall, we find that in harder-hit MSAs, skill requirements increase

[37] Note that even though observations are firm-MSA-year cells, *the investment change is at the firm level, regardless of location*. This is a necessary restriction of the Compustat data, which exists only for the firm and not individual establishments; for comparability, we aggregate sites in the HH data to the firm level, weighting by site employment. When we instead measure investment change at the firm-MSA level in the HH data, the results are qualitatively similar for most skill outcomes. However, both for comparability with the Compustat measure and to avoid additional noise from more demanding match criteria, we prefer defining investment change at the firm level. As before, for PCs, we normalize this difference by average employment in the pre-period. To limit the influence of extreme outliers in the PCs measure, we trim the top and bottom 2.5 percent of firms in the full HH database, which amounts to roughly 4 percent of weighted observations in our regressions.

Panel A. PCs (HH)



Panel B. Capital holdings (Compustat)

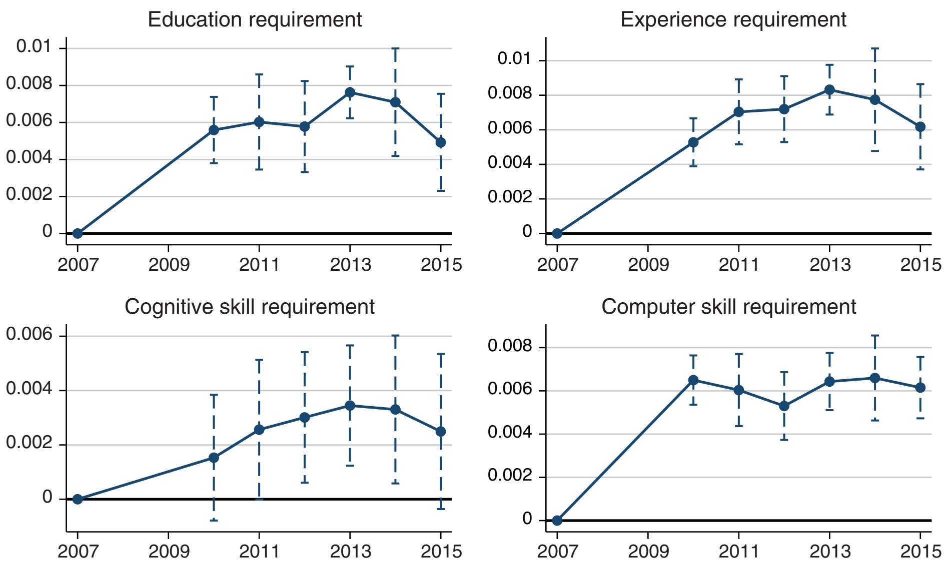


Figure 5. Differential Upskilling by 90–10 Change in Firm Capital Investments

Notes: We regress the firm-MSA-level 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 the firm-level capital change. We also control for year fixed effects and MSA characteristics (see equation (3)). Graph plots the coefficients on the triple interactions, fitted to the 90–10 differential in firm capital change, and 95 percent confidence intervals. The capital change variable is the firm level change in average PCs (Harte-Hanks) per pre-recession employment between 2010–2014 and 2002–2006. Panel B: The capital change variable is the ratio of firm-level average capital holdings (Compustat) in 2010–2014 to holdings in 2002–2006.

by roughly 30 to 50 percent more in high-investment firms than in low-investment firms, and these differentials hold over the post-recession period.

We find quantitatively similar effects when using the Compustat PPENT measure (panel B). For example, in harder-hit MSAs, high-investment firms increase the likelihood of specifying an education requirement by 0.6 to 0.8 percentage points, relative to low-investment firms. This reflects roughly 35 percent greater responsiveness in upskilling. Results for the other skills variables are comparable, with most impacts significant at the 1 percent level.

Thus, throughout our sample period, firms with larger increases in capital stock around the time of the Great Recession also had larger increases in their posted skill requirements. These patterns are consistent with both human and physical capital deepening at the firm level.

V. Routine Occupations

Thus far, we have provided evidence that MSAs more severely affected by the Great Recession experienced persistent increases in the skill demand of job postings as well as greater increases in capital. Moreover, the upskilling and capital investment occurred within the same firms. Both these findings are consistent with episodic restructuring. In this section we explore additional predictions of an RBTC-style restructuring: whether upskilling is more prevalent in more-routine occupations, and related trends in employment and wages for these occupations.

Indeed, the literature on job polarization has successfully linked employment and wage shifts across occupations to the tasks performed by workers in the occupations. Wages and employment have fallen for occupations in the middle of the skill distribution, which, being the most routine, are the kinds of occupations that can be replaced by machines or overseas labor.[38] Autor (2014) and Jaimovich and Siu (2015) have noted that employment continued to shift away from middle-skill occupations in the Great Recession. Our BG data afford the unique opportunity to measure changes in skill requirements within occupations, while the bulk of work on polarization has measured shifts in employment and wages only across occupations. Therefore, we next ask whether upskilling was relatively concentrated *within* routine occupations, the very jobs thought to be most affected by technological change in recent decades.

To determine an occupation's routineness, we use Acemoglu and Autor's (2011) routine-cognitive and routine-manual indices, derived from O*NET (see online Appendix A.6). These indices provide continuous scores based on the intensity of routine tasks performed, are simple to create, distinguish between tasks that use mental and physical capacities, and have been used in several other papers (e.g., Aaronson

[38] The original work by Autor, Levy, and Murnane (2003)—henceforth, ALM—uses the US Department of Labor's (1977) *Dictionary of Occupational Titles* (DOT) to categorize tasks (and indirectly occupations) into nonroutine manual, routine manual, routine cognitive, and nonroutine cognitive. They chose this categorization, arguing that new technologies can successfully replace American workers performing routine, algorithmic tasks, and are complementary to nonroutine, cognitive/analytical functions. Indeed, this grouping successfully predicted employment changes in the 1990s and has been used in a number of subsequent papers, including Autor, Katz, and Kearney (2008).

and Phelan 2017; Keister and Lewandowski 2017).[39] Routine-cognitive tasks tend to be clustered in clerical, administrative, and sales occupations, while routine-manual tasks tend to be found in production and operative occupations. As a whole, employment in both types of occupations has been declining for at least the past two decades (Acemoglu and Autor 2011).

We begin by examining changes in skill requirements as a function of these routine index scores and the Bartik shock. To simplify our analysis, we focus on the top quartile of routine-cognitive and routine-manual occupations. The general pattern of results is similar when we allow for finer distinctions. We estimate regressions of the following form, where $Routine_o^i$ is an indicator equal to 1 if occupation, o, is in the top quartile of categorization, i, where $i \in \{cognitive, manual\}$. Similar to equation (3), we do not include the main effect of $Routine_o^i$ because of the first-difference specification at the occupation-MSA level. The parameter vector α_2 in equation (4) thus captures the additional effect of the shock, each year, for top-quartile routine occupations relative to the effect in occupations in the bottom three quartiles of the relevant routineness index. Henceforth, for exposition, we will refer to these top-quartile occupations as routine-cognitive or routine-manual, as appropriate. Formally,

$$(4) \quad outcome_{omt} - outcome_{om07}$$
$$= \alpha_0 + [shock_m \times I^t]\,\alpha_1 + [shock_m \times I^t \times Routine_o^i]\,\alpha_2 + I^t + X_m\beta + \varepsilon_{omt}.$$

Figure 6 (and online Appendix Table C3) plots estimates of α_2 for each routineness index for the four skill requirements. The coefficients for routine-cognitive occupations are indicated with blue circles, while coefficients for routine-manual occupations (estimated with separate regressions) are shown as maroon squares.

The figure's primary pattern is a greater degree of upskilling in routine-cognitive occupations: these estimates are positive, statistically significant, and persistent in all cases (except for experience in 2015). For example, the blue circle in the top left panel in 2010 indicates that in hard-hit MSAs, job posts for routine-cognitive occupations saw about a 0.5 percentage point larger increase in the probability of having an education requirement, relative to other occupations. For 2012 through 2015, routine-cognitive occupations saw a roughly 1 percentage point larger increase. Comparing these differential impacts to the baseline within-occupation upskilling effects (Table 2), we find that routine-cognitive occupations were approximately 25 (education/experience) to 50 percent (cognitive/computer) more responsive than the average occupation.

In contrast, routine-manual occupations do not exhibit a persistent differential in upskilling. In fact, in the case of cognitive and computer skills, these occupations experience relative downskilling compared to occupations that are not

[39] The Acemoglu and Autor (AA) measures use O*Net (the successor of DOT) to essentially update the original categorization of ALM. Some papers in the literature (e.g., Autor and Dorn 2013; Autor, Dorn, and Hanson 2015) use a simpler routine-manual-abstract categorization (based on the original ALM categories) that does not allow for a distinction between routine-manual and routine-cognitive occupations; we find this distinction to be important. Jaimovich and Siu (2015) use broad occupation categories to generate their binary routine classification. For our purposes, the AA measures are preferable because they allow for finer (continuous) distinctions. The Spearman correlation between our adapted AA measures and the Jaimovich and Siu measures is 0.66 for routine manual but only 0.21 for routine cognitive, indicating that the AA measures likely avoid some miscategorization inherent in the binary definition.

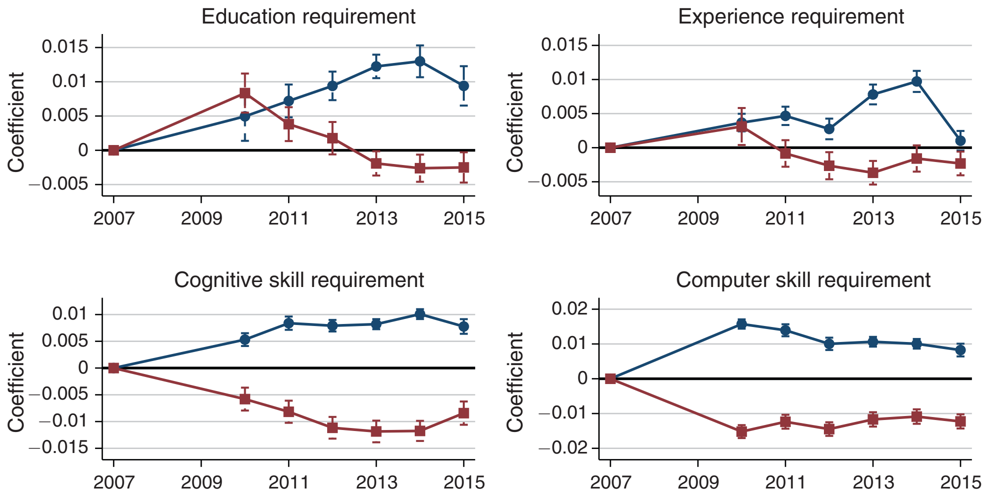


Figure 6. Differential Upskilling for Routine Occupations

Notes: We regress the occupation-MSA-level 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 whether the occupation is routine. We also control for year fixed effects and MSA characteristics (see equation (4)). Graph plots the coefficients on the triple interactions, and 95 percent confidence intervals. The routineness measures are whether the occupation is in the top quartile of routine-cognitive or routine-manual index scores based on Acemolgu and Autor (2011).

routine-manual. (That is, routine-manual occupations upskill less than other occupations.) For education and experience requirements, routine-manual occupations do exhibit temporary differential upskilling, indicated by positive and significant point estimates in 2010 that converge to zero (or negative values) over the next few years. This could reflect opportunistic behavior on the part of firms during a slack market that quickly fades when markets recover.

Upskilling thus appears to be relatively concentrated within routine-cognitive jobs. Our hypothesized explanation for this pattern is that the recession accelerated technological adoption, but that some types of jobs (routine-cognitive ones) could be made more complementary to the new technology with additional human capital, while labor for other types of jobs (routine-manual ones) was more subject to substitution by the new technology. For example, the use of data analytics may make a salesperson more productive by allowing her to better target customers' needs, but software alone will not close a sale: a salesperson capable of using the software is still needed to do the job. On the other hand, machine-vision technology may render obsolete the manual inspection of parts on an assembly line, essentially replacing that job.[40]

To investigate this paradigm, we turn to the implications for employment and wages. If firms do not seek greater skills for routine-manual jobs because those jobs can be substituted with technology more readily than work with it, we would expect firms to disproportionately shed these types of jobs through layoffs,

[40] Indeed, Hawkins, Michaels, and Oh (2015) present recent evidence of this type of capital-labor substitution in the Korean manufacturing sector.

with little employment recovery over time. Since firms do seek greater skill for routine-cognitive jobs, these workers may complement new technology, and if so, their productivity and relative wages should rise. (Predictions for relative wages of routine-manual jobs and relative employment (or job loss) for routine-cognitive jobs are less clear cut, and depend on product demand.)

We explore all three margins, involuntary separations, relative employment, and wages, for routine-cognitive and routine-manual occupations. We examine the rate of involuntary job loss in the population (not just the unemployed), as measured in the CPS by the propensity to report being a job loser. For employment and wages, we use Occupational Employment Statistics (OES) data. Both datasets allow us to capture trends back to 2000, and the earlier years help to check the validity of our identifying assumption, that harder-hit MSAs would have been on a similar trend, in terms of skill demand, if not for the Great Recession. (See online Appendix A.7 for details on sample construction and an analysis of the overall impact of the Bartik shock on these outcomes.)

In Figure 7, we focus on the differential impacts of the Bartik shock on layoffs, employment, and wages for routine-manual (red squares) and routine-cognitive (blue circles) occupations.[41]

Beginning with the top left panel, we find evidence of a large differential layoff effect for routine-manual occupations. At the peak in 2009, individuals whose current or most recent job was in a routine-manual occupation suffer an additional 1.5 ppt increase in involuntary separations, relative to those not in routine-manual occupations, due to a 90–10 percentile MSA shock. For comparison, the same-sized shock increased the probability of having been laid off for those not in routine-manual occupations by 0.8 percentage points in 2009 (see column 1 of online Appendix Table C4 for the full regression output); that is, individuals in routine-manual occupations experienced nearly triple the chance of involuntary separation as did individuals in other occupations. Although routine-cognitive occupations also experience a statistically significant differential increase, the magnitude is modest.[42] Importantly, there appears to be little pre-trend for either routine occupation type, as, except for a tiny blip in 2003, the layoff rate differential is close to zero in all years from 2000 to 2007.

The top right panel (and columns 10 and 11 of online Appendix Table C1) shows how the share of MSA employment in each type of routine occupation varies with the Bartik shock. Following the Great Recession, there is a large and persistent drop in routine-manual employment and a steady and modest rise in routine-cognitive employment.[43] At its trough, the employment share of routine-manual occupations fell by about 2 percentage points more in harder-hit MSAs, recovering only one-half

[41] OES data are based on a three-year moving average, so annual snapshots are not independent and trends are likely smoother than true annual snapshots would be. We have confirmed that this trait does not substantively affect our estimates, as our results do not change appreciably if we use data for every third year (which is independent) instead of annually. Additionally, we get similar results for employment and wages using the CPS or ACS, albeit with fewer included MSAs (CPS) or data years (Census/ACS). We prefer the use of OES for these outcomes for its fuller coverage across occupations, MSAs, and time.

[42] It is possible, but not central to our argument, that workers laid off from a routine-cognitive job have an easier time finding reemployment and thus do not report their current status as laid off.

[43] For this result, we estimate versions of equation (1), using as dependent variables the share of employment in the MSA (relative to 2007) that is routine-cognitive or routine-manual.

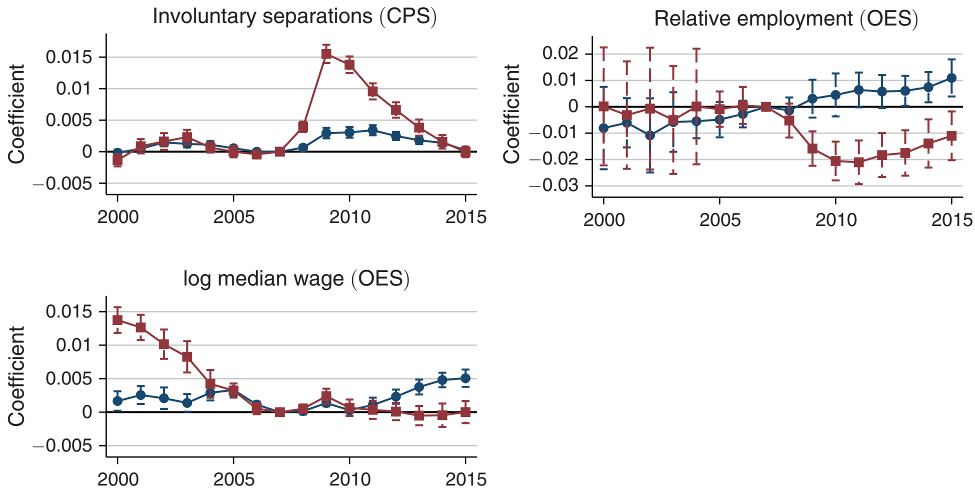


Figure 7. Differential Employment and Wage Effects for Routine Occupations

Notes: Top left and bottom panels plot coefficients on the triple interactions of shock-year-routine (see equation (4) and Figure 6). Top right plots coefficients on shock-by-year, where the dependent variable is the MSA change in the employment share of routine occupations (see equation (1)). All regressions control for year fixed effects and MSA characteristics; we also include 95 percent confidence intervals. The routineness measures are whether the occupation is in the top quartile of routine-cognitive or routine-manual index scores based on Acemolgu and Autor (2011).

of this gap by the end of the sample period. In contrast, routine-cognitive occupations differentially rise as a share of employment in harder-hit MSAs, (or, more aptly, experience smaller magnitude losses in employment share, relative to less hard-hit MSAs) though only modestly. Also, unlike for routine-manual occupations, it is harder to rule out a pre-trend, although it is small and generally statistically insignificant. This pair of results is generally consistent with Jaimovich and Siu (2015), who show that employment in routine occupations as a whole fell episodically, and more so in harder-hit US states, in each of the past three recessions and did not recover fully.

The bottom left panel (and column 2 of online Appendix Table C4) shows the differential impact on log median hourly wages. For routine-cognitive occupations, there is a slight but persistent rise in wages in harder-hit MSAs beginning after 2010. By 2015, the median routine-cognitive worker in a hard-hit MSA has experienced 0.5 percent faster wage growth than a worker in a job that was not routine cognitive. Conversely, routine-manual occupations exhibit almost no post-recession change; wages evolve similarly in the subsequent period regardless of the MSA shock. In the single major exception to the absence of pre-trending, wages for routine-manual jobs were differentially trending downward before the Great Recession in areas that would experience a more severe shock, even though relative employment trended similarly, suggesting other factors (such as declining unionization) were possibly involved.

The sharpest predictions of our hypothesis (episodic increases in layoffs and persistent decreases in employment share for routine-manual workers; and increases in wages for routine-cognitive workers) are borne out by the data, and for these outcomes there is little evidence of differential pre-trending.

To summarize, in harder-hit MSAs routine-manual occupations experience a sharp increase in layoff risk but there is no evidence of upskilling; rather, there appears to be relative downskilling accompanied by employment losses and flat wages. For these occupations, the story is therefore consistent with firms' substitution of technology for labor. This is the traditional view exhibited also in the polarization literature: employment losses concentrated in occupations we expect to be most readily replaceable by machines. Our contribution is to show that these changes appear episodic around the Great Recession, though we acknowledge that secular relative wage losses preceded the employment shock.

In contrast to this conventional view of labor substitution, routine-cognitive occupations in hard-hit MSAs surprisingly exhibit only a modest increase in layoffs and no loss in employment share, relative to other occupations. These changes were concomitant with a pronounced increase in upskilling. Even as the elevated differential risk of layoff declined, the differential in upskilling persisted, and was met with modest relative wage and employment growth after the recession. This pattern is quite consistent with an intensive margin restructuring due to technological adoption that effectively shifts out the labor demand curve.

These results are especially enlightening, given recent findings by Beaudry, Green, and Sand (2014, 2016) that more-educated workers have increased their presence in lower-skilled jobs since 2000. They term this shift, along with stagnating employment in cognitive occupations, the "great reversal" in the demand for cognitive skill (see also Castex and Dechter 2014). They hypothesize that lessened demand for cognitive occupations induces college graduates to take jobs lower in the skill distribution, squeezing out less-educated workers who formerly held these jobs. In light of the evidence above, we propose that any declining demand in cognitive occupations was accompanied by an increased demand for cognitive skill *within* routine-task occupations, and this shift accelerated in the Great Recession. Even as employment has shifted away from routine occupations, the tasks performed in the routine occupations that remain may be becoming less routine and more cognitive. Our work thus highlights a complementary hypothesis for why high-skilled workers are increasingly found in lower-skilled occupations: these latter occupations are becoming more skilled (and more highly paid), and it is possible that less-skilled workers are displaced because they are unable to perform the new duties required.

VI. Conclusion

During the recovery following the Great Recession, anecdotal evidence suggested that the composition of new hires shifted toward higher-skilled workers, resulting in many workers being "overeducated" for their jobs (Burning Glass Technologies 2014). However, it was not clear how broad, deep, or enduring these effects were, or the extent to which they were driven by labor supply or labor demand responses. In particular, firms may have treated the recession as a time of "cleansing," enabling them to restructure their production in a manner consistent with routine-biased technological change.

In this paper we draw upon detailed job postings data to provide comprehensive, broad-based evidence of upskilling (firms demanding higher-skilled workers) when the local economy suffers a recession. Using empirical skill measures that reflect what the discipline has learned about technological change and task-based production over the past 20 years (Autor, Levy, and Murnane 2003; Brynjolfsson and McAfee 2011), we show that job postings in harder-hit MSAs experienced larger increases in their education, experience, cognitive, and computer requirements following the Great Recession. These increases primarily reflected changes in demand *within*, and not across, occupations. Furthermore, skill requirements remained elevated through the end of our sample in 2015, even as most measures of labor market conditions had converged back to their pre-recession levels. Importantly, we find that the increases in skill requirements are accompanied by increases in capital investments, both at the MSA and firm levels. We also show that upskilling is relatively concentrated in routine-cognitive occupations, which exhibit modest wage growth as well. In contrast, routine-manual occupations in harder-hit MSAs exhibit a sharp relative decline in employment share following the Great Recession.

We argue that the most likely explanation for this body of results is that the Great Recession did indeed provide firms a catalyst to restructure production according to a paradigm of routine-biased technological change. While firms may respond to changes in labor market conditions through posted skill requirements for a variety of other reasons, these cannot rationalize our full body of findings. For example, firms may worry that a flood of applicants early in the recovery will create a "bottleneck" in screening, and therefore raise requirements to signal that certain (unwanted) applicants need not apply. Alternatively, firms that typically cannot attract (or afford) more-skilled workers in a tight labor market may opportunistically seek them out in a slack one. However, while both of these cyclical behaviors may have been important early in the recovery, they cannot generate persistent, within-firm increases in skill requirements that stand up to controls for the availability of labor by skill group, occur concomitantly with greater investment in multiple measures of physical capital, and are concentrated in the types of occupations acknowledged to be most susceptible to routine-biased technological change. While it is possible that labor markets have been slower to recover than indicators such as employment growth, the unemployment rate, and education-specific employment-population ratios indicate, it is telling that we find little overall convergence in skill requirements as markets improve, even though the data *do* indicate such convergence in some (e.g., routine-manual) occupations.

Simply put, the evidence supports that shifts in skill requirements reflect technologically-driven changes in the means of production, not just changes in whom firms seek to hire. Our work is thus consistent with the important, but suggestive, evidence provided by Jaimovich and Siu (2015) that the vast majority of employment lost in routine occupations was lost during recessions and never recovered. It also contributes to the many models in macroeconomics that assume adjustment costs and imply that recessions will be times of "cleansing" in terms of production (Schumpeter 1939; Koenders and Rogerson 2005; Berger 2012). As hypothesized by many, these kinds of episodic, productivity-enhancing changes can result in jobless recovery. Our findings are thus extremely relevant for policymakers, who allocate billions of taxpayer dollars to subsidize workers' job searches in a downturn.

We also demonstrate how electronic job postings data can provide a unique opportunity to understand real-time changes in skill demand, both across and within occupations. This level of detail can provide new insight relative to earlier literature. For example, our result that routine-cognitive occupations are apparently becoming higher skilled and more productive can help to clarify studies by Beaudry, Green, and Sand (2014, 2016) and others documenting the "great reversal" in demand for cognitive skill. While it may be the case that employment in high-skill occupations did not grow, on average, over the past decade, our results show that cognitive workers still retain a substantial advantage over the low-skilled. They are drawn into formerly middle-skill jobs, which are becoming higher-skilled. This is indicated by the persistence in both the relative upskilling and wage growth in routine-cognitive occupations located in harder-hit MSAs. Our findings can thus help explain why skilled workers still earn a premium in the labor market even though the returns to cognitive occupations appear to have diminished.

The US economy has seen remarkable changes over the past 30 years, brought on by the computer revolution and globalization. These changes have led to great increases in productivity and wealth, but the benefits have not been shared across all workers. Indeed, mounting evidence suggests that a large population of workers, formerly employed in routine-task jobs, have suffered permanent labor market, health, and social consequences from structural changes in the economy (Autor et al. 2014; Foote and Ryan 2014; Pierce and Schott 2016; Autor, Dorn, and Hanson 2017). Our results highlight that a worker's ability to adjust to these changes may be especially difficult because the changes are episodic, concentrated in recessions. Thus, large numbers of workers can find their skills depreciated at the same time. This is perhaps evident in the stair-step declines in male labor force participation that have tended to be concentrated around recessions (Moffitt 2012; Foote and Ryan 2014). If the changes to production instead occurred more gradually, workers would still need to be retrained, but over a longer time period, and on a much smaller scale at any given time. Future policy work should be directed at understanding how to reallocate workers on a large scale following a recession.

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