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Did the Computer Revolution shift the fortunes of U.S. cities? Technology shocks and the geography of new jobs☆

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ABSTRACT

This paper shows how the Computer Revolution of the 1980s shifted the economic trajectories of U.S. cities. Examining the emergence of new occupational titles in official census classifications, we document a sharp reversal in the skill content of new jobs. While technological change was biased towards routine skills throughout the 1970s, new job titles mainly appeared in occupations and industries that required abstract skills after 1980. This reversal is also reflected in the geography of new jobs. Following the Computer Revolution, the creation of new jobs shifted towards cities with endowments of analytical and interactive skills. Our results suggest that the recent divergence of U.S. cities can in part be explained by the complementarities between new technologies and skill endowments.

1. Introduction

Why is prosperity so unevenly distributed across the United States? In *The New Geography of Jobs*, Moretti (2012) argues that America's "Great Divergence" has its origins in the 1980s, when the abundance of skills started to dictate the fortunes of U.S. cities. Over recent decades, initially skilled areas have attracted even more skilled workers, explaining in part why income convergence in the United States has come to halt (Barro et al., 1991; Berry and Glaeser, 2005; Ganong and Shoag, 2012). While there is an ongoing debate about the driving forces behind this phenomenon, one explanation points towards a tendency of skilled cities to adopt technology in ways that create new jobs for more skilled workers (Beaudry et al., 2010; Lin, 2011).

In this paper, we show how a previously undocumented shift in the skill content of new jobs, following the Computer Revolution of the 1980s, has altered patterns of new job creation across U.S. cities.[1] Our analysis builds on the intuition of Jacobs (1969), suggesting that the economic trajectories of cities are shaped by their deployment of skills to create new jobs as old ones are made redundant by the arrival of new technologies. For example, during the early part of the 20th century, factory mechanization increased the demand for machine operatives performing routine tasks (Goldin and Katz, 1998). In contrast, over recent decades, computer-controlled equipment has substituted for a wide range of routine work—including the jobs of machine operatives, bookkeepers and telephone operators—while creating new jobs that require abstract skills, such as computer programming and software engineering (Autor et al., 2003).

To identify the appearance of new jobs, we exploit the inadvertent paper trail left by new technologies in new occupational titles from Lin (2011). Paired with data on job task descriptions from the 1977 Fourth Edition of the Dictionary of Occupational Titles (DOT), allowing us to infer on-the-job skill requirements, we show that new jobs mainly appeared in occupations and industries that required routine skills prior to the 1980s. Nevertheless, over the course of the 1980s, new jobs became more abstract in nature—that is, they gradually required more analytical and interactive skills. Using data from the Current Population Survey (CPS) supplements, we show that this shift is intimately associated with the Computer Revolution: after 1980, new jobs mainly appeared in occupations and industries that extensively adopted computers.

Fig. 1 documents the impact of the changing skill content of new jobs on cities, showing a sharp reversal in the relationship between abstract skill endowments and new job creation across locations.

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[1] Throughout the paper, we refer to the period commencing with the arrival of the personal computer (PC) in the 1980s and continuing with the development of the World Wide Web in the 1990s as the "Computer Revolution".

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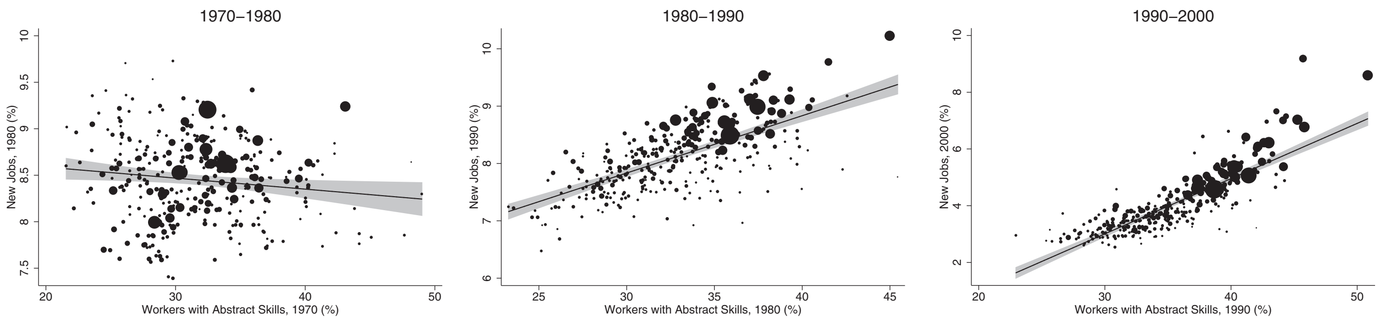
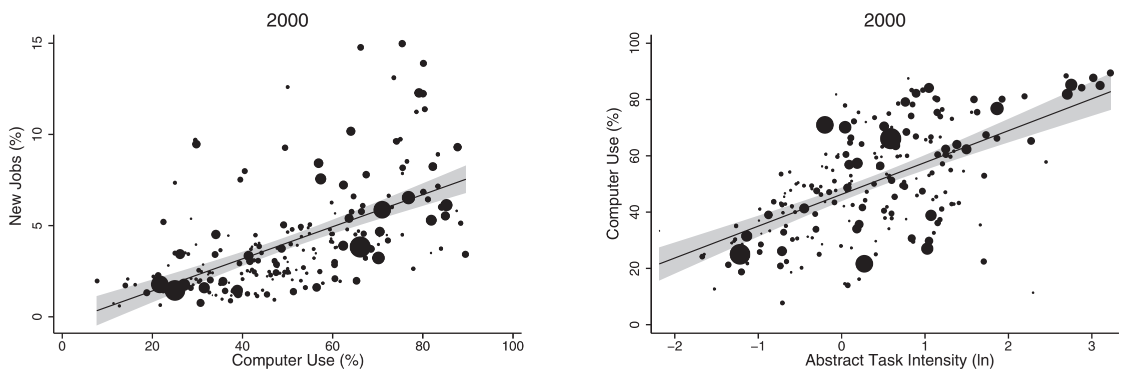


Fig. 1. Abstract skills and new job creation in U.S. cities, 1970–2000.



(a) New Jobs and Computer Use

(b) Computer Use and Abstract Skills

Fig. 2. Abstract skills, computer use, and new jobs, 2000.

Throughout the 1970s, abstract cities experienced slightly slower new job creation. Following the diffusion of the PC in the 1980s and 1990s, however, the very same cities adapted faster by creating new jobs. While this pattern resonates with an aggregate shift in the U.S. labor market towards jobs that demand abstract skills, it also reveals substantial variation in rates of adaption to the Computer Revolution across U.S. cities. (See Fig. 2.)

In our main empirical analysis, we begin by showing that differences in computer adoption can account for much of the variation in new job creation across cities and that computers were more extensively adopted in cities with an abundance of abstract skills. We next examine the relationship between abstract skills and new job creation across U.S. cities before and after the Computer Revolution. Doing so, we show that while there is virtually no relationship between abstract skills and new job creation prior to the Computer Revolution, there is a strikingly strong relationship from the 1980s onwards. This relationship is robust to alternative explanations, emphasizing the role of differences in city size, the relative supply of college-educated workers, and cities' reliance on manufacturing. (See Table 6.)

Our paper relates to several literatures. First, our paper is most closely related to Beaudry et al. (2010), documenting that cities with an abundance of college-educated workers experienced more rapid computer adoption, and Lin (2011), finding that cities where college-educated workers are plentiful have created more new jobs since the 1980s. Nevertheless, evidence suggests that workers' skills are intrinsically related to the type of tasks they perform (e.g., Murnane et al. (1995); Ingram and Neumann (2006); Poletaev and Robinson (2008); and Gathmann and Schönberg (2010). Following Bacolod et al. (2009), arguing that if workers are assigned to jobs in a hedonic market clearing process, worker's skills can be inferred from the tasks they perform on their jobs, we therefore make use of the 1977 DOT to examine the complementarities between a wider range of skills and the arrival of new technologies.[2] Thus, in contrast to Beaudry et al. (2010) and Lin (2011) that equate workers' skills with their educational attainment, we differentiate between different skills based on detailed descriptions of the actual tasks performed by workers, allowing us to (i) reveal a previously undocumented shift in the skill content of new jobs, and (ii) document a direct link between the Computer Revolution of the 1980s and the changing geography of new jobs across U.S. cities.[3]

Our findings also contribute to a growing literature that examines the polarization of labor markets over recent decades, resulting from changes in the task composition of occupations and the reallocation of workers away from routine task-intensive jobs (Goos and Manning, 2007; Goos et al., 2009; Frey and Osborne, 2013; Michaels et al., 2013; Goos et al., 2014).[4] In tandem with computers substituting for labor in routine tasks, this literature documents an increased labor input of abstract tasks, which computers complement (Autor et al., 2003). We add to this literature by showing that the changing skill content of new jobs constitutes a potentially important margin of task change, that can partly account for the increased labor input of abstract tasks within occupations (e.g., Spitz-Oener (2006).

[2] See Autor et al. (2003); Ingram and Neumann (2006); Bacolod et al. (2009); Autor and Dorn (2013) and Michaels et al. (2013) for other examples of use of the DOTs.

[3] Furthermore, an important limitation with single technology measurements, such as the PC adoption measure employed by Beaudry et al. (2010), is that they do not capture the relative impact of different technologies on labor markets. New jobs, on the other hand, allow us to examine the relationship between new means of production both before and after the Computer Revolution.

[4] In particular, Autor and Dorn (2013) show that, across U.S. local labor markets, investments in computer equipment led to the displacement of workers performing routine tasks, leading to a "hollowing out" of employment. By contrast, we find that in cities with endowments of abstract skills, computer technologies are implemented in new jobs.

More broadly, our results relate to work showing that skills have come to dictate U.S. city fortunes (Glaeser et al., 1995; Simon and Nardinelli, 1996, 2002; Simon, 2004; Glaeser and Saiz, 2004; Glaeser et al., 2012; Kok and Weel, 2014; Berger and Frey, 2015), and a strand of this literature documenting that initially skilled cities have become more skilled over time (Berry and Glaeser, 2005; Moretti, 2012). We build on this literature, showing that the divergence in human capital levels across U.S. cities partly can be explained by the changing geography of new jobs: since the Computer Revolution, cities that were dense in abstract skills have benefited differentially by creating more abstract task-intensive new jobs. This finding also provides an empirical counterpart to the mechanisms described in Duranton (2007), suggesting that cities slowly move up and down the urban hierarchy in response to technology shocks that lead to the churning of industries across cities.

The remainder of this paper is structured as follows. In the following section, we describe our data and further outline our approach to measuring skills and new job creation in U.S. cities. In Section 3, we show that new jobs mainly appeared in industries and occupations that require abstract skills after 1980, and Section 4 documents the shift in new job creation across U.S. cities. Finally, in Section 5, we derive some concluding remarks.

2. Data and measurement

To capture the appearance of new jobs and measure the skill endowments of U.S. cities, we construct our dataset from primarily three sources: worker-level data from the Census Integrated Public Use Microdata Series (IPUMS) (Ruggles et al., 2010), occupation-level data on new job titles from Lin (2011), and information on job tasks from the 1977 DOT.

2.1. Census data

We use the 1970 (1%), 1980 (5%), 1990 (5%) and 2000 (5%) IPUMS samples, that report workers' occupation and industry, educational attainment, location of residence and demographic characteristics (Ruggles et al., 2010). We restrict our sample to non-institutionalized workers, aged 18–65, outside of Alaska and Hawaii, and with occupational responses that we are able to match with data from the 1977 DOT. To measure computer use, we also collect data from the CPS 1989 (October) and 2001 (September) supplements, which allows us to estimate the share of workers that used a computer on the job in 1989 and 2001, by detailed industry and occupation. To examine the spatial variation in new job creation, we assign workers in the IPUMS samples to consistently defined commuting zones (CZs), using crosswalks from Autor and Dorn (2013). CZ boundaries reflect local labor markets, based on county-level commuting patterns from the 1990 census (Tolbert and Sizer, 1996). In the empirical analysis, we focus on the 321 urban CZs, which we interchangeably refer to as “cities” throughout the paper.[5]

2.2. New job titles

To identify the appearance of new job titles, Lin (2011) meticulously compares changes in the occupational categorization of the DOTs and the Alphabetical Index of Occupations, using three classification revisions involving five title catalogs. Specifically, the first comparison is between the DOT's third (1965) and fourth (1977) editions, where 1152 new titles (out of 12,695 total titles) appeared for the first time. The second comparison uses the DOT's fourth (1977) and revised fourth (1991) editions, yielding 830 (12,741) new titles. Lastly, the third comparison identifies new titles from the 1990 and 2000 editions of the Alphabetical Index of Occupations, which yields 840 (30,900) new titles.[6] New occupational titles are identified at the five- or nine-digit levels (for example, chat room host/monitor), whereas occupations are reported at the three-digit level in the IPUMS samples (for example, the corresponding occupation network systems and data communication analysts). Collapsing the five- and nine-digit titles to their respective detailed occupation results in three lists that contain the share of new occupational titles in each detailed occupation, that appeared for the first time in the 1970s, 1980s and 1990s, respectively (see Table 1).[7] We match these three lists to worker-level data from the 1980, 1990 and 2000 IPUMS extracts, using the crosswalks developed by Autor and Dorn (2013) to create consistently defined occupations across census years.

2.3. 1977 DOT

We merge IPUMS and new jobs data with task measures from the 1977 Fourth Edition DOT, that contains detailed information on a large number of job tasks for more than 12,000 occupations, with the input of each task assigned a value between 1 and 10.[8] To reduce the dimensionality, we follow Autor et al. (2003) in using the original DOT data collapsed into measures of three task inputs: abstract, routine and manual. Importantly, while computer technology constitutes a complement to workers performing abstract tasks, it substitutes for routine tasks, with ambiguous effects on manual tasks.

Abstract tasks involve interactive, problem-solving, complex communication, managerial and analytic reasoning skills, and are captured by the average of the Direction, Control and Planning of activities (DCP) and GED Math (MATH) measures in the DOT. Occupations with high inputs of abstract tasks are, for example, computer software developers, industrial engineers and a wide range of managerial occupations. Routine tasks, on the other hand, correspond to tasks that can be simplified into rule-based activities, and are measured by the average of Set limits, Tolerances and Standards and Finger Dexterity. Routine occupations include bank tellers, typists and assembly work. Finally, manual task inputs are measured by eye–hand–foot coordination for which computer technology neither constitutes a substitute or complement. Examples of occupations that require considerable manual inputs are bus drivers, electric power installers and cartographers. We merge the occupation-level data on abstract, routine and manual task inputs with the worker-level data in the IPUMS extracts, again using the occupational crosswalks developed by Autor and Dorn (2013).

2.3.1. Measuring cities' abstract, manual and routine skills

To measure cities' endowments of abstract skills, we calculate the share of each city's workers that are employed in jobs that intensively involve abstract tasks. For each detailed occupation we use data from the DOT on the (log) input of abstract tasks, with higher values indicating a stronger complementarity with computer technology. In a next step, we define a subset of occupations that are relatively intensive in abstract tasks, similar to the procedure in Autor and Dorn (2013). Formally, letting Ω correspond to the 75th percentile of the employment-

[5] Urban status is defined based on whether a CZ intersects a metropolitan statistical area. Results presented below are very similar in a sample that also includes rural CZs and are available from the authors upon request.

[6] For simplicity, we refer to these periods as the 1970s (1965–1977), 1980s (1977–1991), and 1990s (1990–2000) throughout the paper. See Lin (2011) for a detailed discussion of the procedures used to identify truly new job titles.

[7] Since we do not observe whether a worker is actually employed in new jobs, this measure relies on the assumption that workers are equally distributed across occupational titles within detailed occupations. While such an assumption is likely violated, note that it is unlikely to produce a bias in a cross-sectional comparison of cities.

[8] To accurately capture the changing job tasks performed by U.S. workers, the 1977 revision of the DOTs included more than 2000 new occupational definitions, in turn based on 75,000 on-site job analysis studies.

Table 1
Examples of new jobs, 1970–2000.

Panel A. New jobs in 1980		Panel B. New jobs in 1990		Panel C. New jobs in 2000	
Detailed occupation	% new titles	Detailed occupation	% new titles	Detailed occupation	% new titles
Engineers: agricultural	75.0	Computer systems analysts and scientists	80.0	Network systems and data communication analysts	96.7
Engineers: nuclear	75.0	Radiologic technicians	70.0	Computer support specialists	86.4
Supervisors, guards	75.0	Pharmacists	66.7	Network and computer systems administrators	83.3
Management analysts	66.7	Tool programmers, numerical control	66.7	Computer software engineers	80.0
Sheriffs, bailiffs, and other law enforcement officers	61.5	Parking lot attendants	66.7	Database administrators	76.9
Marine and naval architects	57.1	Engineers: nuclear	60.0	Computer and information systems managers	76.5
Welfare service aides	50.0	Peripheral equipment operators	50.0	Radiation therapists	75.0
Construction laborers	50.0	Health record technologists and technicians	50.0	Computer programmers	59.1
Supervisors, carpenters and related workers	50.0	Urban planners	50.0	Logisticians	50.0
Supervisors, personal service occupations	46.7	Archivists and curators	47.1	Computer hardware engineers	50.0

Notes: This table reports the 10 detailed occupations with the highest fraction of new occupational titles appearing in each respective decade, based on data from Lin (2011). Panel C shows, for example, that 80% of the job titles in the detailed occupation computer software engineers observed in 2000 did not exist in 1990.

weighted abstract task input (ATI_o) across all occupations in 1980, we create an indicator variable:

$$I_{io} = \begin{matrix} 1 & if & ATI_o > \Omega \\ 0 & if & ATI_o < \Omega \end{matrix} \tag{1}$$

taking the value 1 if a worker is employed in a abstract task-intensive occupation and 0 otherwise. Letting L_c denote the size of the labor force in city c, we then calculate the endowment of abstract skills (A^S_{ct}) of each city as the share of workers that are employed in occupations intensive in abstract tasks:

$$A^S_{ct} = \frac{\sum_{i \in c} I_{io}}{L_c}. \tag{2}$$

In principle, there are many different ways to construct this skill measure. Below reported results are, however, robust to several alternative cutoffs (Ω) and insensitive to alternative ways to calculate relative task intensities (ATI_o).[9] Reassuringly, many cities with historically high shares of abstract work are also commonly associated with subsequent adaptation to computer technologies: San Francisco, the fourth most abstract city in 1970, for example, was the most computer-intensive city in the U.S. by 1990 (Doms and Lewis, 2005).

3. The Computer Revolution and the changing skill content of new jobs

3.1. Background: the Computer Revolution

Over the course of the twentieth century, technological change has fundamentally altered the type of tasks performed by workers, in turn shifting the demand for skills. During the first half of the century, the workplace entered a wave of mechanization, with dictaphones, calculators, address machines, etc. (Beniger, 1986; Cortada, 2000). Importantly, these office machines reduced the cost of routine information processing tasks and increased the demand for the complementary factor—that is, high school educated office workers (Goldin and Katz, 1995). Similarly, recent advances in computing augments the demand for workers performing such tasks, but they also permit them to be automated.

Beginning in the 1950s, mainframe computers were adopted by most larger establishments, allowing new software technologies and database management systems to be introduced (Bresnahan, 1999). While these technologies augmented relatively skilled scientists and engineers, such jobs constituted only a fraction of the U.S. labor force. At the same time, as late as the 1970s, computer technologies still complemented a variety of routine work.[10] Automation of such jobs, however, was first permitted in the early 1980s, following the introduction of the PC with its word processing and spreadsheet functions, substituting for copy typist occupations and workers performing repetitive calculations. Furthermore, with the development of the World Wide Web and the growth of e-commerce throughout the 1990s, labor services were increasingly delivered over the Internet, substituting for the work of reservation clerks and cashiers.

Over the course of the 1980s, computers successively became a general purpose technology, transforming the nature of work in virtually all occupations and industries. The Computer Revolution of the 1980s thus marks an important turning point, with the spread of computer technologies contributing to a subsequent decline in the demand for a wide range of routine work (Levy and Murnane, 2004), in turn leading to a "hollowing-out" of labor markets in nearly every advanced economy as middle-skill jobs disappeared (Autor et al., 2006; Autor and Dorn, 2013; Goos and Manning, 2007; Goos et al., 2009). Yet, while computer technology has displaced workers in many middle-skill routine jobs, it has also increased the demand for workers performing abstract tasks—a shift that is evident within industries, occupations and skill groups (Autor et al., 2003).

Computer technologies have however not merely shifted the composition of employment between and within existing industrial and occupational classifications, but also resulted in the appearance of entirely new types of jobs. Bresnahan (1999), p.398, among others, persuasively argues that, to benefit from the general-purpose characteristics of computers, firms had to "invent new ways of organizing work, new job definitions, and new management structures."[11] These changes have been complementary to workers with analytical or interactive skills, as is evident from the new jobs that appeared in the wake of the Computer Revolution, such as database administrators and web designers. Since the early 1980s, more than 1500 new job titles appeared in the updates of occupational classifications (Lin, 2011), bearing witness to a pervasive restructuring of U.S. industries, firms and workplaces.

[9] For instance, using other cutoffs such as the median or the 80th percentile yields very similar results. In the working paper version, we also included manual and routine tasks in our abstract task-intensity measure, producing very similar results to those presented below (see Berger and Frey (2014)).

[10] For example, throughout the 1970s, reservation clerks working at distant terminals became increasingly connected to computers, and data entry clerks benefited from video display terminals, gradually replacing punch card data entry (Bresnahan, 1999).

[11] Also see Brynjolfsson and Hitt (2003) that uses firm-level data to show that while investments in computers raise productivity and output growth in the short run, the impacts of computerization are substantially larger over a longer time horizon as it requires time-consuming organizational changes.

3.2. Computers and the changing skill content of new jobs

3.2.1. Qualitative evidence: examples of new jobs

Table 1 lists the 10 detailed occupations with the highest fraction of new job titles by decade. In the 1980s, the first computer-related occupations appear, with some 80% of all job titles in the detailed occupation computer systems analysts and scientists emerging since the 1970s. By the 1990s, virtually all occupations are a direct result of the Computer Revolution: 8 of the 10 occupations with the highest share of new job titles, such as computer software engineers and database administrators, are directly associated with the diffusion of computer technology. Other occupations, such as radiation therapist, similarly underwent significant restructuring following technological advances.[12]

Although these qualitative indicators suggest that new jobs increasingly appeared in computer-related occupations, they do not capture any systematic relationship between the diffusion of computers and new job creation. We next provide regression evidence showing that new jobs mainly appeared in industries and occupations that extensively adopted computers and that computer use increased in sectors that required abstract skills after 1980.

3.2.2. Abstract skills, computer use and new jobs

To examine the relationship between the adoption of computers and new job creation, we rely on the CPS computer use supplements that records if a worker uses a computer on the job. Although this is a narrow measure of the diffusion of computer technology, it provides a straightforward way to measure differences in computer use across detailed industries and occupations.[13] For each detailed occupation and industry, we calculate the share of employed workers aged 18–65 that answered yes to the question: "Do you use a computer directly at work?", matching the computer use data from the CPS 1989 (October) and 2001 (September) supplements to the share of new job titles observed in 1991 and 2000 respectively (see Section 2.2).

Fig. 1a graphs the positive industry-level relationship between the average share of new job titles and the share of workers that use a computer on the job around 2000. Furthermore, Fig. 1b shows that computer use is substantially higher in industries that are intensive in abstract skills. To examine the statistical significance of these correlations, Table 2 reports the corresponding OLS regressions:

$$\Delta NJ_{it} = \alpha + \delta_1 C_{it} + \varepsilon_{it} \tag{3}$$

$$C_{it} = \alpha + \delta_2 A^T_{it} + \varepsilon_{it} \tag{4}$$

where ΔNJ_{it} is the share of new job titles in detailed industry or occupation i in year t, C_{it} is the percentage of workers who used a computer on the job, and A^T_{it} is the average (log) input of abstract tasks. These relationships are all statistically significant and evident both in 1990 and 2000. Moreover, the differential adoption of computers can account for a substantial part of cross-industry/occupation differences in new job creation: increasing the share of workers using a computer on the job by one standard deviation is associated with a 0.3–0.7 standard deviation increase in new job titles in the 1980s and 1990s.

Although these correlations should be interpreted with care, they provide suggestive evidence of a link between abstract skills, the implementation of computer technology, and the appearance of new jobs. To further support this argument, we next provide cross-industry/occupation evidence, showing that new jobs increasingly appeared in sectors intensive in abstract tasks following the Computer Revolution, while new jobs were mainly created in routine sectors prior to the diffusion of computer technology.

Table 2
Abstract skills, computer use, and new jobs, 1980–2000.

	Detailed occupations		Detailed industries	
	1990	2000	1990	2000
	(1)	(2)	(3)	(4)
Panel A. Outcome: share employed in new jobs (ΔNJ_{it})				
Computer use (C_{it})	0.126***	0.112**	0.120***	0.129***
	[0.290]	[0.426]	[0.607]	[0.672]
R-squared	0.12	0.08	0.27	0.43
Panel B. Outcome: computer use (C_{it})				
Abstract tasks (A^T_{it})	0.096***	0.120***	0.085***	0.094***
	[0.537]	[0.602]	[0.620]	[0.685]
R-squared	0.24	0.36	0.37	0.46

Notes: This table reports OLS estimates of Eqs. (3) and (4). Occupations are defined as 330 consistent defined occupations from Autor and Dorn (2013) and industries are defined according to a consistent 1990 classification scheme from IPUMS. Standardized β-coefficients are presented in brackets and statistical significance based on robust standard errors is denoted by: *** p <0.01, ** p<0.05, * p<0.10.

3.2.3. The changing skill content of new jobs

Did new jobs become increasingly abstract in nature after the Computer Revolution of the 1980s? To answer this question, we examine whether sectors that were initially more intensive in abstract tasks experienced larger additions of new jobs before and after the Computer Revolution. We regress the average share of new job titles (ΔNJ_{it}) in detailed industry/occupation i on the average (log) input of abstract (A^T_i), manual (M^T_i) and routine (R^T_i) tasks in that industry/occupation in by the beginning of the period (t-10)[14]:

$$\Delta NJ_{it} = \alpha + \delta_1 A^T_{it-10} + \delta_2 M^T_{it-10} + \delta_3 R^T_{it-10} + \varepsilon_{it} \tag{5}$$

As shown in Table 3, industries and occupations that were more intensive in abstract tasks experienced systematically larger additions of new jobs after 1980, while new jobs typically appeared in routine-intensive sectors prior to the Computer Revolution. Panel A reports results from regressing the share of new job titles on the input of abstract tasks, and panel B displays results when using the abstract, routine, and manual task inputs separately. In columns 1–3, we show that new job titles were more prevalent in occupations that were intensive in abstract tasks in 1990 and 2000, but not in 1980, which reflects a relative decrease in routine-intensive new titles and a simultaneous increase in abstract occupations (panel B). Columns 4–6 reveal a similar reversal across detailed industries, consistent with the argument that computer adoption is more likely to generate new jobs in occupations and industries that intensively rely on abstract skills.[15]

Taken together, results reported in this section shed light on a nuanced shift in the skill content of new jobs around 1980. Moreover,

[12] In 1974, the magnetic resonance imaging (MRI) machine, a device that uses magnetic fields and radio waves to form images of the body used for medical diagnosis, was patented. Six years later, in 1980, the first clinically useful MRI body scan was performed, leading the way for the proliferation of MRI scanning techniques. The result is reflected in the appearance of a new occupational title: Special procedures technologist, MRI, where workers operate and monitor diagnostic imaging equipment.

[13] As pointed out by Beaudry et al. (2010), focusing on the diffusion of PCs can be motivated in at least two ways. Firstly, spending on PCs exceeded that of other computers by more than 90% in the 1990s. Secondly, investments in other types of computer equipment or information technology are likely to be highly correlated with spending on PCs in this period.

[14] Following Autor and Dorn (2013), occupations are defined as 330 consistently defined detailed occupations and detailed industries are defined according to a consistent 1990 classification scheme from IPUMS.

[15] A potential shortcoming is that we do not observe the skill content of new jobs, nor how the task content of occupations and industries change along intensive margins over time (c.f., Autor et al. (2003)). However, under the assumption that new job titles are more intensive in abstract skills than existing titles, this would result in a downward biased estimate of the abstract task-intensity of new jobs after 1980. Moreover, these observed shifts in the skill content of new jobs over time reduce concerns that new jobs are always more abstract-intensive than old jobs, before they can be subdivided and routinized.

Table 3
The changing skill content of new jobs, 1970–2000.

	Detailed occupations			Detailed industries		
	1980	1990	2000	1980	1990	2000
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Outcome: share employed in new jobs (ΔNJ_{it})						
Abstract Tasks (A^T_{t-10})	0.001	0.010***	0.006**	−0.002	0.009**	0.012***
	[0.012]	[0.171]	[0.168]	[−0.089]	[0.249]	[0.315]
R-squared	0.00	0.05	0.02	0.01	0.05	0.10
Panel B. Outcome: share employed in new jobs (ΔNJ_{it})						
Abstract tasks (A^T_{t-10})	0.008	0.032***	0.037***	0.028*	0.095***	0.086***
	[0.066]	[0.198]	[0.385]	[0.265]	[0.677]	[0.606]
Manual tasks (M^T_{t-10})	−0.001	−0.004	0.004	0.010	0.013	−0.000
	[−0.010]	[−0.055]	[0.085]	[0.223]	[0.208]	[−0.002]
Routine tasks (R^T_{t-10})	0.026**	−0.001	−0.005	0.049***	−0.019	0.002
	[0.169]	[−0.006]	[−0.037]	[0.451]	[−0.131]	[0.012]
R-squared	0.04	0.08	0.12	0.23	0.27	0.31

Notes: This table reports OLS estimates from Eq. (5), regressing the share of workers in new jobs per detailed occupation/industry on the initial (1970, 1980, 1990) log input of abstract, manual and routine tasks. Occupations are defined as 330 consistent detailed occupations and industries are defined according to a consistent 1990 classification scheme from the IPUMS. Standardized coefficients are presented in brackets and statistical significance based on robust standard errors is denoted by: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

they suggest that the creation of new types of jobs are an important margin of task change, that partly accounts for the increased labor inputs of abstract tasks in industries experiencing rapid computerization (Autor et al., 2003; Spitz-Oener, 2006). In the remainder of the paper, we turn to examine how this shift affected patterns of new job creation across U.S. cities.

4. The changing geography of new jobs: empirical evidence

In this section, we first document that cities that extensively adopted computers after 1980 also experienced substantially more rapid new job creation, and that computers were mainly adopted in cities with an abundance of abstract skills. Subsequently, we show that prior to the Computer Revolution there is no relationship between cities' share of abstract skills and new job creation, whereas after the Computer Revolution there is a strong link between analytical and interactive skills and the appearance of new jobs.

4.1. Abstract skills, computer adoption, and new jobs

We begin by documenting that cities extensively adopting computers also experienced more rapid new job creation and that computers were more extensively adopted in cities with high levels of abstract skills. Using the city-level measure of PC adoption of Beaudry et al. (2010), we estimate simple OLS regressions, where the share of workers employed in new jobs (ΔNJ_{ct}) is explained by differential adoption of computers (ΔC_{ct})[16]:

$$\Delta NJ_{ct} = \alpha_s + \lambda_t + \delta \Delta C_{ct} + \varepsilon_{ct}. \tag{6}$$

Table 4, panel A, shows that the share of workers that shifted into new jobs were substantially higher in cities that extensively adopted computers; this relationship is evident both in the 1980s and 1990s (columns 1 and 2). Estimated differences are furthermore economically substantial: a one standard deviation increase in computer adoption is associated with a 0.3–0.6 standard deviation increase in new job creation and between a third and half of the cross-city variation in new job creation between 1980 and 2000 is accounted for by differences in computer adoption. Panel B presents estimates where we instead use the (Beaudry et al., 2010) PC adoption measure as the outcome variable regressed on each city's initial level of abstract skills. These estimates show that PC adoption was considerably higher in cities with more abstract jobs, reflecting the complementarity between computer technology and such skills.[17] We next proceed by documenting that the Computer Revolution represents a watershed in the location of new job creation across US cities.

4.2. New job creation before and after the computer revolution

To examine the changing relationship between cities' endowments of abstract skills and new job creation, we examine decade-by-decade changes in the creation of new jobs and initial cross-city variation in abstract skills. Table 5 presents OLS estimates of:

$$\Delta NJ_{cst} = \gamma_s + \delta A^S_{cst-10} + \varepsilon_{cst} \tag{7}$$

where ΔNJ_{cst} is the share of workers in new jobs in city c in state s in year t and A^S_{cst-10} is each city's initial share of abstract skills, γ_s capture state-specific shocks and ε_{cst} is an error term. For the statistical inference, we cluster standard errors at the state-level.

Table 5 shows that prior to the Computer Revolution of the 1980s there is no relationship between a city's initial endowment of abstract skills and new job creation (column 1). After 1980, however, there is a positive and statistically significant relationship between a city's initial abstract skills and the share of workers that transition into new jobs in both the 1980s and 1990s (columns 2 and 3). Panel B shows that these results are similar when including a full set of state fixed effects, reducing concerns that our estimates reflect state-wide shifts in new job creation. Panel C calculates for each city its initial level of abstract, manual and routine skills respectively, where the city-level measure of manual and routine skills are defined analogously to the definition of abstract skills, corresponding to the share of workers that are employed in jobs that fall in the upper quartile of the employment-weighted 1980 task distribution (see Section 2.3.1). Prior to the Computer Revolution, there is again little evidence that cities with an

[16] Beaudry et al. (2010) use firm-level survey data for some 160,000 firms to calculate the average PCs per employee per metropolitan area, adjusted for three-digit industry-by-establishment size classes, which yields a residual measure of computer use. Autor and Dorn (2013) match the Beaudry et al. (2010) data to the level of CZs, which we merge with our new jobs data. Note that data is missing for one CZ, which constitutes a negligible share of the total population.

[17] Autor and Dorn (2013) instead argue that computers were adopted in local labor markets that were intensive in routine tasks, for which computer equipment substitutes. However, controlling for each city's initial share of routine-intensive jobs, using the RTI measure developed in Autor and Dorn (2013)), leaves the link between abstract skills and computer adoption unaffected, suggesting that these measures capture two distinctly different phenomena: that is, the substitution for routine tasks by computers and the complementarity between abstract skills and computers.

Table 4
The changing skill content of new jobs, 1970–2000.

Period:	1980–1990	1990–2000
	(1)	(2)
Panel A. Outcome: share employed in new jobs (ΔNJ_{ct})		
PC adoption (ΔC_{ct})	0.076***	0.064***
	(0.584)	(0.284)
R-squared	0.55	0.31
Panel B. Outcome: PC adoption (ΔC_{ct})		
Abstract skills (A^S_{t-10})	0.793***	0.377***
	(0.680)	(0.361)
R-squared	0.58	0.41

Notes: This table reports OLS estimates from Eq. (6) across 320 U.S. cities. In panel A, the outcome is the share of workers employed in new jobs and in panel B the outcome is a residual measure of computer adoption from Beaudry et al. (2010). Standardized coefficients are presented in parentheses and statistical significance based on standard errors clustered at the state-level is denoted by: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 5
Abstract skills, computer adoption, and new jobs in U.S. cities, 1980–2000.

Outcome: share employed in new jobs (ΔNJ_{cst})			
Year:	1980	1990	2000
	(1)	(2)	(3)
Panel A. Baseline			
Abstract skills (A^S_{cst-10})	−0.012	0.100***	0.195***
	(−0.133)	(0.667)	(0.833)
R-squared	0.018	0.444	0.694
Panel B. State FE			
Abstract skills (A^S_{cst-10})	−0.003	0.130***	0.213***
	(−0.037)	(0.870)	(0.913)
R-squared	0.588	0.691	0.789
Panel C. Abstract, manual and routine skills			
Abstract skills (A^S_{cst-10})	−0.003	0.084***	0.148***
	(−0.037)	(0.558)	(0.635)
Manual skills (M^S_{cst-10})	−0.001	−0.060***	−0.089***
	(−0.007)	(−0.437)	(−0.345)
Routine skills (R^S_{cst-10})	−0.000	−0.048***	0.021
	(−0.003)	(−0.214)	(0.045)
R-squared	0.59	0.76	0.83

Notes: This table reports OLS estimates from Eq. (7), where the outcome is the share of workers employed in new jobs at the end of each respective decade across 321 U.S. cities. Robust standardized coefficients are presented in parentheses and statistical significance based on standard errors clustered at the state-level is denoted by: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

abundance of abstract skills experienced more rapid new job creation, while larger shares of manual and routine skills were associated with lower levels of new job creation throughout the 1980s and 1990s.

In all, the results presented in this section provide evidence that U.S. cities with endowments of abstract skills experienced higher rates of new job creation after 1980, when computers diffused in the workplace. We next examine alternative explanations for this shift, showing that concentrations of abstract skills constitute the most important predictor of new job creation.

4.2.1. Alternative explanations for patterns of new job creation after 1980

This section examines three alternative explanations for our results: that new job creation may have shifted to larger cities, that our results reflect the fact that college-educated workers are more prevalent in cities with an abundance of abstract skills, and that manufacturing decline may be an important omitted factor.[18] Although these factors are important, they do not account for the relationship between abstract skills and new job creation documented in the previous section. For brevity, we report estimates of Eq. (7) where we stack new job creation in the two decades 1980–1990 and 1990–2000, with an added year fixed effect.[19]

Table 6
Abstract skills and new job creation in U.S. cities, 1970–2000.

	Outcome: share of workers employed in new jobs, 1980–2000				
	(1)	(2)	(3)	(4)	(5)
Abstract skills (A^S_{t-10})	0.153***	0.128***	0.101***	0.162***	0.088***
	(0.301)	(0.252)	(0.199)	(0.318)	(0.174)
City size (ln)		0.003***			0.002***
		(0.127)			(0.117)
College-educated workers (ln)			0.010***		0.009***
			(0.139)		(0.128)
$\Delta Manufacturing_t$				−0.033***	−0.019**
				(−0.057)	(−0.033)
R-squared	0.94	0.95	0.94	0.94	0.96

Notes: This table reports OLS estimates from Eq. (7) where we stack the two decades 1980–1990 and 1990–2000, with an added year fixed effect, yielding a total of 642 city–year observations. Robust standardized coefficients are presented in parentheses and statistical significance based on standard errors clustered at the state-level is denoted by: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

A large literature document that larger cities benefit from agglomeration economies, including knowledge spillovers and more efficient matching (Rosenthal and Strange, 2001; Duranton and Puga, 2004; Ellison et al., 2010; Bleakley and Lin, 2012). Jobs intensive in abstract skills are also typically more prevalent in larger cities, meaning that city size may constitute an important omitted variable in our analysis.[20] Yet, controlling for city size leaves the link between abstract skills and new job creation largely unaffected (column 2), while the positive and statistically significant relationship between city size and new job creation reaffirms the finding of Lin (2011), that new jobs are typically created in larger cities.

A growing body of work further emphasizes the relative supply of skilled workers as a key determinant of technology adoption. In particular, Beaudry et al. (2010) show that U.S. cities with an initial relative abundance of college-educated workers adopted computers more extensively. Because college-educated workers are more likely to be observed in occupations intensive in abstract tasks, the link between abstract skills and new job creation may reflect the presence of more educated workers. However, although a higher relative supply of college-educated workers is associated with more rapid new job creation after 1980, controlling for the relative supply of college-educated workers only slightly reduces the magnitude of our estimates (column 3), suggesting that our measure of abstract skills captures something distinctly different than educational attainment.[21]

Finally, to examine the impact of manufacturing decline, column 4 controls for decadal changes in the share of each city's employment in manufacturing. Importantly, cities that experienced large relative declines in manufacturing employment also exhibited lower rates of new job creation, speaking to past findings showing that old manufacturing cities have struggled to reinvent themselves (Glaeser and Saiz, 2004). Nevertheless, this correlation does not affect the relationship between

[18] In the working paper version (Berger and Frey, 2014), we provide a broader set of robustness checks, showing that the results are robust: (i) in a wide variety of subsamples; (ii) using residual variation in new job creation, net of individual-level observable characteristics; (iii) controlling for a wider range of city characteristics; and (iv) focusing on differences in new job creation within major occupational groups.

[19] Results are nearly identical when instead examining these alternative explanations for each individual decade.

[20] In 2000, for example, the raw correlation between our abstract skill measure and (log) city size is 44%.

[21] To estimate the share of college-educated workers, we calculate the share of workers, aged above 25, with at least three years of college education, plus one half of workers with some (1–2 years) college education and calculate the relative supply as the ratio of the log of the college to non-college population. Using alternative measures, such as the percentage of the population with a college degree or average years of education, yields very similar results.

a city's abstract skills and new job creation. As a last robustness check, column 5 simultaneously controls for all three factors, which does little to affect our main finding: that there is a strong link between abstract skills and new job creation after 1980.

5. Concluding remarks

Although the Computer Revolution has arrived everywhere, U.S. cities have fared very differently over recent decades—while some cities have experienced rapid growth, others have virtually disappeared (Glaeser et al., 1995). In this paper, we explore how cities' skill endowments shaped their economic trajectories over the course of three decades. Doing so, we show how a previously undocumented shift in the skill content of new jobs, following the Computer Revolution of the 1980s, has altered patterns of new job creation across U.S. cities. Throughout the 1970s, when technological change was biased towards routine tasks, abstract cities experienced relatively slow technological adaptation, measured by the prevalence of new jobs. By contrast, in the 1980s and 1990s, cities with endowments of abstract skills adapted to the Computer Revolution by creating substantially more new jobs, relative to cities that specialized in routine or manual work. Such an interpretation and the gist of our empirical estimates are consistent with the popular perceptions of urban success and decline in the U.S., emphasizing the relative decline of cities such as Buffalo, Cleveland or Detroit—cities that all historically specialized in routine work.

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