TECHNOLOGY SHOCKS AND URBAN EVOLUTIONS:
DID THE COMPUTER REVOLUTION SHIFT THE FORTUNES OF U.S. CITIES?*

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Abstract

In this paper, we show how differential rates of adaptation to an economy-wide technology shock—the *Computer Revolution* of the 1980s—have altered patterns in urban development across U.S. cities. Specifically, we document that the diffusion of computer technologies has contributed to a reversal in the task content of new occupational titles: while new types of work were still associated with routine tasks in the 1970s, additions of new work have mainly appeared in cognitive occupations and industries since 1980. Cities that historically specialized in cognitive work benefited differentially by shifting workers into new occupations, experiencing simultaneous relative increases in population, human capital and wages, subsequent to the Computer Revolution. Our results suggest that the recent divergence of U.S. cities can partly be explained by the complementarity of new technologies and historical skill endowments.

JEL: R11, O31, O33

Keywords: Technological change, urban development, new work

I Introduction

Throughout history disruptive technology shocks have shifted the fortunes of corporations, cities and nations. While it is widely understood that long-run economic growth depends on the application of new technologies in production (Solow, 1956; Romer, 1990; Mokyr, 1990), Joseph Schumpeter (1942, p. 84) famously noted that new technologies sometimes strike "not at the margins of the profits and the outputs of the existing firms but at their foundations and their very lives."

A vast literature documents the disruptive impacts new technologies may have on companies and industries, in turn causing some cities to prosper and others to decay.[1] For example,

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[1]Christensen (1997) shows in some detail how disruptive technologies have reshaped a wide range of industries, from computer hardware to steel manufacturing, causing leading companies to fail in the process. For example, beginning in the 1960s, the U.S. steel industry experienced a major disruption as mini mills replaced the integrated steel mill. Between 1975 and 1987, the total number of integrated steel mills declined by almost 50 percent. The result was not only a restructuring of the steel industry, but a decline in the population of leading steel cities, such as Pittsburgh and Youngstown (Brezis and Krugman, 1997).

in 1879, when George Eastman invented the emulsion-coating machine in Rochester, New York City was the center of the photographic industry. The Eastman Kodak company soon took over the market for photographic film and Rochester replaced New York as the leading city in film production. In the 1960s, Kodak was still the largest employer in Rochester with over 60,000 employees. Yet, as many other companies, Kodak did not manage the transition to digital photography. When the company finally shut down its largest research and production facility in Rochester, known as Kodak Park, the population of Rochester had not just witnessed the decline of an industrial giant, but the decline of an entire city. As Kodak's workforce dropped by almost 80 percent between 1993 and 2006, Rochester rapidly lost in population.

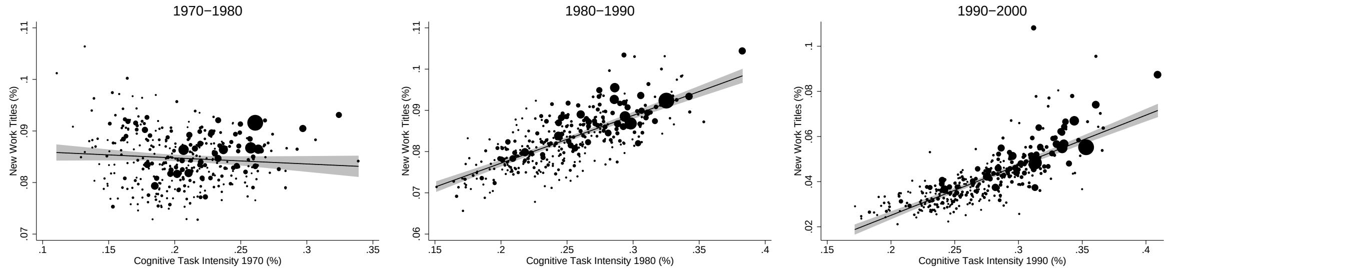
In this paper, we show how differential rates of adaptation to an economy-wide technology shock—the *Computer Revolution*—has altered U.S. city fortunes.[2] Over recent decades, computer-controlled equipment has substituted for a wide range of routine work—including the jobs of bookkeepers, cashiers and telephone operators—while creating new work that require cognitive skills, such as computer programming and software engineering. Our analysis builds on the simple intuition that new types of work emerge in cities where new technologies augment existing skills of workers, while cities that remain locked into old work, for which these technologies substitute, may experience relative declines. To systematically capture the extent of technological adaptation, we exploit the inadvertent paper trail left by new technologies in the appearance of new occupational titles—what we interchangeably refer to as *new work*—capturing when and how they are implemented and their diffusion across industries, firms and occupations. Doing so, we follow influential urban theorists such as Jane Jacobs, placing new work at the heart of urban development, arguing that:

> "If we were to measure the economic development rate of a city, we could not do so just by measuring its output in a year or any group of years. We would have to measure, rather, the additions of new work to its older output, over a period of time, and the ratio of the new work to the old work [...] A city's ability to maintain a high development rate is what staves off stagnation and allows the city to continue to prosper." (Jacobs, 1969, p.94f)

To measure new work, we use data on new occupational titles from Lin (2011). Paired with data on job task requirements from the fourth edition of the Dictionary of Occupational Titles (DOTs), we show that new work during the 1970s mainly appeared in occupations and industries that required routine skills. Nevertheless, as the number of computers-in-use surged from 3.1 to 51.3 million over the course of the 1980s (Computer Industry Almenac, 1996), new work became increasingly associated with cognitive skills. Importantly, using data from the Current Population Survey (CPS) supplements, we find the shifting task content of technological change to be associated with the use of computers, which account for a substantial fraction of new work in the U.S. economy over this period.

Against this background, we investigate how the Computer Revolution has shaped the economic trajectories of U.S. cities. Figure 1 documents the central result of our paper: a sharp reversal in the creation of new work across locations, implying a shift in the comparative advantage of cities in adapting to new technologies. Throughout the 1960s and 1970s, when technological change was biased towards routine tasks, cognitive cities—with historical endowments of cognitive skills—experienced slower technological adaptation. Following

[2]We refer to the period starting with the arrival of the personal computer (PC) in the 1980s, and continuing through the development of the World Wide Web and e-commerce in the 1990s, as the Computer Revolution.



Notes: These figures show the fraction of workers that were employed in jobs that did not exist by the beginning of each respective decade against the initial share of each city's workers employed in occupations that were intensive in cognitive tasks across 363 U.S. cities. Circle size is proportional to each city's population. Solid lines correspond to fitted values from an OLS regression, with 95 percent confidence bounds shaded in grey. See section III.A for a more detailed description of the underlying data.

Figure 1: The Reversal in New Work Across U.S. Cities, 1970-2000.

the diffusion of the PC in the 1980s and 1990s, however, the very same cities adapted faster by shifting labour into new work.[3] While this finding resonates with an aggregate shift in the U.S. labor market towards jobs that demand cognitive skills (Autor *et al.*, 2003), it also reveals substantial variation in technological adaptation across U.S. cities.

In our empirical analysis, we examine the extent to which differential patterns in technological adaptation can be predicted by historical differences in skills across cities. Similar to a difference-in-differences design, our empirical strategy exploits two sources of variation: historical variation in skill endowments and changes in the task content of technological change over time, plausibly exogenous to the individual city. Importantly, exploiting cross-sectional variation in skills, determined prior to the Computer Revolution, and aggregate variation in the task content of technological change, limits the set of potentially confounding factors.

Our regression results reveal substantially faster technological adaptation in cities historically endowed with cognitive skills after 1980, relative to cities specializing in routine or manual work. These effects are also evident within major occupational groups and when using worker-level data to adjust for selection into new work. Relative differences in technological adaptation seem to have accelerated in the 1990s, consistent with models of technology diffusion that emphasize adoption spillovers. Our results are robust to controlling for several alternative explanations, such as variation in human capital, industry variety or historical differences in cities' reliance on manufacturing.

In tandem with higher technological adaptation after 1980, cities historically endowed with cognitive skills experienced relative increases in population and the fraction of the population with college degrees. Moreover, after having experienced slower wage growth through the 1970s, relative patterns of wage growth reversed in cognitive cities after 1980, mirroring the reversal in technological adaptation shown in Figure 1. These results do not seem to reflect differential growth patterns of cities in the Sun Belt, differences in human capital across cities, sorting of individual workers, nor cities' industrial past. Overall, we conclude that an understanding of the mechanisms underlying technological adaptation is important, also to understand urban evolutions.

[3]For example, Pottsville—a city with a historical dependence on non-cognitive work, such as coal mining and textile manufacturing—was one of the fastest adapters to technological progress before the Computer Revolution, but has been one of the least dynamic cities since. By contrast, Champaign, the center of the *Silicon Prairie*, specialized in cognitive work early on, attracting technology companies such as IBM, Sony and Yahoo!. Having been a relatively slow adapter to technological change before 1980, Champaign has been one of the fastest adapters since the Computer Revolution.

Our paper relates to several literatures. First, we build on the work of Lin (2011), showing that new technologies translate into new work in cities with a variety of industries and educated workers. We advance these findings by documenting a shift in the type of skills associated with new work, its relationship with the diffusion of computer technology, and subsequent impacts on urban growth patterns.

Second, a growing literature on the task content of employment examines the polarization of labor markets over recent decades (Autor *et al.*, 2003; Goos and Manning, 2007; Goos *et al.*, 2009; Frey and Osborne, 2013; Michaels *et al.*, 2013). Relative to this literature, we focus on new types of work associated with computer technologies, rather than the distributional impact of computers on employment between existing occupations. For example, Autor and Dorn (2013) show that routine cities invest more in computer equipment, leading to the displacement of workers performing routine tasks. By contrast, we find that cognitive cities exhibit higher rates of computer use, as the workplace is reorganized to accommodate the arrival of computer technologies. Our findings thus imply that while routine cities may invest more in computer equipment to substitute for labour, cognitive cities adapt to computer technologies by implementing them in new types of work.[4]

Third, our results relate to work showing that the abundance of skilled labour has come to dictate U.S. city fortunes (Glaeser *et al.* 1995; Simon and Nardinelli 1996, 2002; Glaeser and Saiz 2004; Glaeser *et al.* 2012). In particular, we build on a subset of this literature documenting that initially skill-abundant cities invest more in computer equipment (Beaudry *et al.*, 2010). By linking the concept of skill directly to job tasks in the firm, we show how shifts in the task content of technological change can alter the demand for skills and with it patterns in urban development.[5]

Finally, we provide an empirical counterpart to the mechanisms described in Duranton (2007), suggesting that cities move up and down the size distribution in response to the churning of industries across cities. Consistent with the model of Brezis and Krugman (1997), we find that the success of a city in a traditional technology may put it at a disadvantage in adapting to the arrival of newer and more productive technologies. Our findings thus mirror historical episodes of technology shocks making the comparative advantages of some cities obsolete, causing "upheaval in the urban hierarchy" (Bairoch, 1988).

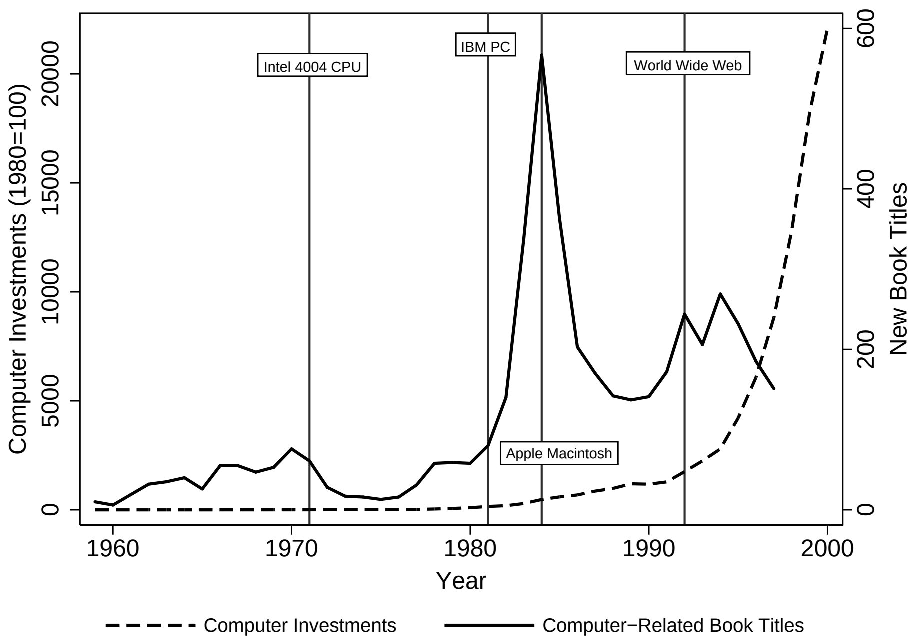
The remainder of this paper is structured as follows. In the following section, we review the relevant literature and state our predictions. In section 2, we describe our data and further outline our approach to measuring task specialization and technological adaptation of cities. Section 3 describes our empirical strategy and documents our main findings. Finally, in section 4, we derive some concluding remarks and implications for urban policy.

II Background and Conceptual Framework

In this section, we provide a brief overview of the Computer Revolution and its importance to the creation of new types of work. To guide our empirical analysis, we then outline a

[4]Furthermore, using a broader measure of technological change allows us to examine the relationship between cognitive skills and technological adaptation, also before the diffusion of the PC.

[5]The productivity of workers' skills is intrinsically related to the type of tasks they perform (e.g., Poletaev and Robinson, 2008; Gathmann and Schönberg, 2010). Accordingly, wages have not increased uniformly among college-educated workers or within other skill groups; when controlling for the soaring returns to cognitive skills since the 1980s, returns to formal education have essentially remained flat (Murnane *et al.*, 1995; Ingram and Neumann, 2006).



Notes: This figure shows how investments in computers and peripheral equipment as well as the appearance of new computer-related book titles surged after 1980. The data is based on Alexopoulos (2011), who kindly made her data on new computer software, hardware and network titles available to us, and data on deflated computer investments from the Bureau of Economic Analysis (http://research.stlouisfed.org/fred2/series/B935RC1A027NBEA).

Figure 2: Charting the Computer Revolution.

simple conceptual framework linking technological adaptation to urban evolutions, emphasizing the role of changing complementarities between new technologies and historical skill endowments.

II.A The Computer Revolution and New Work

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 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. While these technologies augmented relatively skilled scientists and engineers, such jobs constituted only a fraction of the U.S. labour force. At the same time, as late as the 1970s, computer technologies still complemented a variety of routine work. 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).

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 rapid growth of e-commerce throughout the 1990s, labour services were increasingly delivered over the Internet, substituting for the work of reservation clerks and cashiers. Importantly, over the course of the 1980s, computers successively became a general purpose technology, transforming the the nature of work in virtually all occupations and industries. As shown in 2, the early 1980s experienced the first take-off in computer investments and a surge in computer-related book titles. 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).

While computer technology has displaced workers in many middle-skill routine jobs, it has also increased the demand for workers performing cognitive tasks—a shift that is evident within industries, occupations and skill groups (Autor *et al.*, 2003). New 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 work. 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 organising work, new job definitions, and new management structures." These changes have been complementary to workers with cognitive skills, as made evident in the new work that appeared in response to the Computer Revolution.[6] For example, the term "computer" initially referred to an occupation—literally *one who computes*—that originated with the invention of calculus in the eighteenth century. With the advent of the electronic computer, the routine task of performing mathematical operations was gradually transferred to machines, displacing human workers in the process (Grier, 2013). More recently, computer technology has given rise to many new occupations, such as database administrators and web designers, that require cognitive skills. While the disappearance of human computers and the appearance of web designers constitutes two isolated examples of how computer technology have respectively destroyed and created work, the more than 1,500 new job titles that appeared in the occupational classifications following the Computer Revolution bear witness to a pervasive restructuring of U.S. industries, firms and workplaces.[7]

New work has several distinct advantages as a measure of adaptation to new technologies. Relative to diffusion measures of single technologies, such as imports of computer equipment or firm-level computer inventory, it allows us to examine the task content of technological change prior to the Computer Revolution.[8] Patents are another frequently used measure of innovation, capturing a wide range of technologies. Yet, patents have many well-known limi-

[6]Bresnahan *et al.* (2002) provide evidence that firms that implemented ICT also decentralized managerial decision-making, hired more educated workers and increased investments in on-the-job training. See also Doms *et al.* (1997) for evidence on the relationship between computer adoption and human capital.

[7]Lin (2011) compares the 1977 and 1991 editions of the *Dictionary of Occupational Titles*, showing that 830 new job titles appeared during this period; in a similar comparison between the 1990 and 2000 editions of the census *Classified Index of Industries and Occupations*, 840 new titles were documented. See Table 1 for examples of occupations in which new job titles were most prevalent between 1970 and 2000.

[8]For example, Caselli and Coleman (2001), Beaudry *et al.* (2010) and Autor and Dorn (2013) use computer imports and firm-level computer inventory to study the cross-country diffusion of computers and their impact on local labor markets. Furthermore, following Krueger (1993) it is also common to regress individual wages on an indicator capturing whether a worker uses a computer on the job. Below we document that workers using computers on the job are more likely to be found in new types of work.

tations: many important technological breakthroughs are not patented, many patents are never commercialized, patents differ substantially in their technical and economic significance and there is often a long time-lag between the issuance of a patent and the actual implementation of the technology (Griliches, 1990). Although Lin (2011) shows that patents are highly correlated with new work, patents importantly do not convey information about how technologies are implemented in production.[9] New work, on the other hand, reveals information about a broad set of technologies, capturing when and how they are implemented and their diffusion across industries, firms and occupations.[10]

Importantly, measuring technological change by new work allows us to shed light on an empirical conundrum: although the Computer Revolution has arrived everywhere, U.S. cities have have fared very differently over recent decades (Glaeser *et al.*, 1995). While some cities have invested substantially in computer equipment to substitute for labour (Autor and Dorn, 2013), other cities have adapted by implementing computer technology in new types of work (Lin, 2011). To be sure, over recent decades, one side of the story has been computers substituting for labour in routine cities. New work captures the other side of that story—that is, how cognitive cities have adapted to the shifting task content of employment by reorganizing production to move up the urban hierarchy.

II.B Technological Adaptation and Urban Evolutions

Once a new technology is available, the adoption decision is based on firms' weighing of incremental benefits and associated costs; the diffusion rate of that technology is simply the sum of many such decisions across individual firms (Hall and Khan, 2003). A large fraction of the cost of adopting new technologies arises from a lack of information regarding the range of available technologies and their respective profitability, slowing down their diffusion (Griliches, 1957; Mansfield, 1961).[11] By reducing adoption costs, the presence of knowledge spillovers or imitation across firms will result in faster diffusion rates in cities that initially adopt a new technology.[12] Localized learning may further lead to a reversal of fortunes if the accumulated knowledge in cities that specializes in an old technology is not useful for firms adopting a new technology (Brezis and Krugman, 1997).

New work reflects a margin of *adaptation* to new technology, capturing how firms adopt technologies, but also how they are combined with production tasks and the latent skills of their workers into novel bundles of job tasks, manifesting itself as new occupations in the labor market. While computer-controlled equipment has substituted for a number of routine-intensive jobs, it has also augmented cognitive skills. Cities' historical task composition therefore reflect the extent to which jobs in a city is at risk of automation—a higher fraction of

[9]Input measures, such as R&D investments or other innovation expenditure have similar drawbacks when it comes to assessing the rate and direction of technical change, as they do not contain information of how new technologies shape labor markets (Kleinknecht *et al.* 2002).

[10]Bresnahan (1999, p.391) argues that the relevant "mechanism does not work through managers and professionals literally using a computer. Instead, ICT changes the organisation of bureaucratic production at the firm, industry, and even multi-industry level."

[11]A large literature documents the slow diffusion of new technologies (Grübler, 1991; Jovanovic and Lach, 1997; Comin and Mestieri, 2013).

[12]Goolsbee and Klenow (2002) provide evidence of spillovers in computer adoption among individuals. More generally, evidence on informational barriers and the presence of spillovers in technology adoption is particularly evident in the development literature on adoption of high-yielding seed varieties (e.g., Foster and Rosenzweig, 1995; Bandiera and Rasul, 2006; Conley and Udry, 2010).

work intensive in cognitive tasks corresponds to production processes that are more likely to be altered by new work, rather than job displacement.[13] Alternative adaptation mechanisms include differences in the relative supply of skilled workers (Beaudry *et al.*, 2010), industry variety (Duranton and Puga, 2001), or shifts in the final demand towards products requiring cognitive skills in production (Glaeser *et al.*, 2001).[14] We evaluate the empirical plausibility of these mechanisms in the following sections.

Uneven technological adaptation may also be mirrored in changes in population, skills and wages across cities. Changes in population arise from individual workers' migration decisions, in turn reflecting changing perceptions about differences in quality of life and potential labor market outcomes (Sjaastad, 1962). While cities that historically specialized in routine work may experience a decline in employment opportunities, the demand for workers should increase in cities that rely on cognitive tasks. Though decreasing labor demand may lower wages, inducing firms to relocate to lower-cost cities, evidence suggest that adjustment takes place primarily through out-migration (Blanchard and Katz, 1992).[15] To the extent that new work is intensive in cognitive tasks, it will induce mobile workers with complementary skills—that is, educated workers with a comparative advantage in performing cognitive tasks—to relocate to cities dense in such tasks.[16] An inflow of skilled workers would raise average wages through purely compositional effects, by raising the average quality of matches between workers' skills and the changing production tasks of firms, or human capital spillovers (Rauch, 1993; Moretti, 2004).[17]

To summarize, we predict that, after 1980, cities that historically specialized in cognitive tasks experience: (1) more rapid technological adaptation, as computer technologies proliferated through the U.S. economy; (2) growth in population and the share of skilled workers; and (3) higher rates of wage growth.

III Data and Measurement

In this section, we describe the data sources used to measure the task specialization of cities—mirroring their skill endowments—and their creation of new work. We then document that after 1980, new occupational titles were more prevalent in occupations and industries that were intensive in cognitive tasks as well as substantial heterogeneity in task specialization across U.S. cities.

[13] In the presence of spillovers across firms in a city, small initial differences in technological adaptation will also intensify over time.

[14] See Neffke *et al.* (2011, 2012).

[15] Hornbeck (2012) provides evidence from a large regionally confined productivity shock—the *Dust Bowl* of the 1930s—showing that adjustment took place primarily through a permanent out-migration from the most adversely affected areas.

[16] Broadly speaking, this prediction is consistent with the fact that U.S. workers are prone to migrate in response to shifting growth patterns and evidence that skilled workers are particularly mobile (Blanchard and Katz, 1992; Bound and Holzer, 2000).

[17] Nominal wage differences are, however, unlikely reflected in real wage differentials of similar magnitude, as nominal differences are partly or completely offset by higher prices or rents in larger and more skilled cities (Moretti 2013).

III.A Data Sources

To examine the relationship between task specialization, technological adaptation and urban evolutions, we construct our dataset from primarily three sources: (1) micro-level data from the Integrated Public Use Microdata Series (IPUMS); (2) occupation-level data on the appearance of new occupational titles from Lin (2011); and (3) occupational work task data from the 1977 edition of the U.S. Department of Labor's *Dictionary of Occupational Titles* (DOT). Our compiled dataset consists of roughly 11 million observations on workers, the fraction of new occupational titles and the task content of each workers recorded occupation. For our main analysis, we collapse this data to 363 consistently defined cities.

Micro-level Data (IPUMS & CPS)

For our purposes, the IPUMS samples report individuals' occupation and industry, educational attainment, location of residence and demographic characteristics. Specifically, we use the 1970 (1%), 1980 (5%), 1990 (5%) and 2000 (1%) samples (Ruggles *et al.*, 2010); restricted to individuals aged 18-65, outside of Alaska and Hawaii, that do not live in group quarters, and with occupational responses that we are able to match with data from the DOTs. Due to confidentiality restrictions, the census samples does not allow for identification of places with less than 100,000 inhabitants; individuals are therefore assigned to PUMAs, that consist of a combinations of counties so that reported units exceed the confidentiality threshold. Cities are constructed by aggregating PUMAs and county groups, to create consistently defined geographical units of observation over the period 1970 to 2000. Geographical units within the same metropolitan area are aggregated using the 2003 core-based statistical areas (CBSA) of the U.S. Office of Management and Budget, resulting in 363 city aggregates with consistent geographical boundaries over time. Additional data on population and geographical area was derived from the 1972, 1983, and 1994 U.S. Census' City and County Data Books (Haines, 2005).[18]

To measure computer use, we also collect data from the Current Population Survey (CPS) October, 1989 and September, 2001 supplements. For a large sample of workers, these supplements provide individual survey responses to the question: "Do you use a computer at work?" Based on this information we estimate the fraction of workers that used a computer on the job in 1989 and 2001, by three-digit occupation and industry.

New Occupational Titles

The U.S. occupational classifications are periodically updated to reflect the restructuring of the economy and the tasks performed by workers. To identify the appearance of new occupational titles, Lin (2011) meticulously compared changes in the occupational categorization of the DOTs and the census *Classified Index of Industries and Occupations*, using three classification revisions involving five title catalogues.[19] New occupational titles are reported at

[18]We are very grateful to Jeffrey Lin for providing us with a crosswalk between geographical aggregates in the 1970 and subsequent censuses, as well as digitized data from the U.S. Census' City and County Data Books.

[19]Specifically, the first comparison is between the DOT's third (1965) and fourth (1977) editions, where 1,152 new titles out of 12,695 total titles appeared; the second comparison is between the DOT's fourth (1977) and revised fourth (1991) editions, where 830 out of 12,741 titles were new; and the third comparison is between the census Classified Indexes from 1990 and 2000, where 840 out of 12,741 titles had been added since the beginning of the decade. For simplicity, we refer to these periods as the 1970s (1965-1977), 1980s (1977-1991)

the five- or nine-digit levels in the *Classified Indexes* and the DOTs, whereas occupations are reported at the three-digit level in the IPUMS extracts. Collapsing the five- and nine-digit titles to three-digit occupations results in three lists that contain the fraction of new titles in each three-digit occupation, that appeared for the first time in the 1970s, 1980s and 1990s, respectively.[20]

We match these lists to consistently defined occupations from the 1980, 1990 and 2000 census samples, using the crosswalks developed by Autor and Dorn (2013). A potential shortcoming is that new titles may not reflect novel jobs, but rather changing methodologies or a relabeling of existing occupations. In practice, however, detailed supplemental documentation of changing work titles in the U.S. allow for isolating title changes that correspond to actual new titles.

Job Tasks

The DOT was devised by the U.S. Employment Services to ease the matching of job applicants' skills with the production tasks of firms, with further applications in career guidance, employment counseling and related information services. The fourth edition of the DOT, released in 1977, contains detailed information on a large number of job tasks for more than 12,000 occupations, where the input of each task is assigned a numerical value between 1 and 10.[21] To reduce the dimensionality, we follow Autor *et al.* (2003) in using the original DOT data collapsed into measures of three task inputs: cognitive, routine and manual. Importantly, these three measures correspond to tasks that are either complemented by (cognitive), substituted for (routine), or largely unaffected (manual) by computer technologies.

Cognitive tasks—that require problem-solving, complex communication, managerial and quantitative reasoning skills—are measured as the average of the Direction, Control and Planning of activities and GED Math measures in the DOT. Occupations with high inputs of cognitive 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 specified in computer code, and are measured by the average of Set limits, Tolerances and Standards and Finger Dexterity. Routine occupations include bank tellers, typists and medical appliance technicians. 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 vast manual inputs are bus drivers, electric power installers and cartographers. Occupation-level data on cognitive, routine and manual task inputs are crosswalked to the micro-level data in the IPUMS extracts, again using the crosswalks developed by Autor and Dorn (2013).

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and 1990s (1990-2000) throughout the paper.

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

[21]The 1977 revision of the DOTs included more than 2,000 new occupational definitions, in turn based on 75,000 on-site job analysis studies, supplemented by extensive inputs from trade and professional associations to accurately capture the changing job tasks performed by U.S. workers. (See http://www.occupationalinfo.org/front_148.html for more information on the DOTs.)

III.B Computers and the Task Content of New Work

Since the Computer Revolution of the 1980s, the task content of technological change has become increasingly complementary to workers with cognitive skills. In this section, we document that: (1) this shift is evident from a qualitative comparison of occupational titles; (2) that occupations and industries that adopted computers more extensively also exhibited higher fractions of new work; and (3) that cognitive industries and occupations experienced more new work after, but not before, 1980.

Table 1 lists the 10 three-digit occupations with the highest fraction of new work titles by decade. In the 1980s, we find the first computer-related occupations, and by the 1990s, virtually all top 10 occupations are a result of the Computer Revolution: eight of the ten occupations with the highest fraction of new work titles, such as Computer Software Engineers and Database Administrators, are directly associated with computer technologies.

Other occupations, such as Radiation therapist, similarly underwent significant restructuring, following technological advances. For example, the magnetic resonance imaging (MRI) machine, a device that uses magnetic fields and radiowaves to form images of the body used for medical diagnosis, was patented in 1974. 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.[22] Overall, while these qualitative findings suggest that new occupational titles became increasingly associated with computer-related occupations over time, they do not capture any systematic relationship between the diffusion of computers and new types of work.

To examine the relationship between computers and new work, we rely on the CPS computer use supplements. Figure 3a documents our findings: a positive relationship between the average number of new job titles in 2000 and the fraction of workers that use a computer on the job, across three-digit industries. The adjusted R-squared from the regression is 27 percent, meaning that more than a quarter of the variation in new work across industries can be accounted for by differential rates of computer use. Furthermore, Figure 3b shows that computer use is substantially higher in industries that are intensive in cognitive skills. As documented in Table 2, these relationships are all statistically significant and evident both in 1990 and 2000. While these correlations should be interpreted with care, they still provide suggestive evidence of a link between cognitive skills, the implementation of computer technology and the appearance of new types of work.

We turn to examine the task content of new work before and after the advent of the Computer Revolution. Table 3 reports regression results of the fraction of new work and inputs of cognitive, routine and manual tasks, by decade. Importantly, we find that occupations and industries that were more intensive in cognitive tasks experienced systematically larger relative increases in new work after 1980. Panel A reports results using the cognitive task intensity as calculated in (1) and panel B displays the results when using the cognitive, routine and manual task inputs separately. In columns 1-3, we show that new occupational titles were more prevalent in occupations that were intensive in cognitive tasks in 1990 and 2000, but

[22] Similarly, parking lot attendants—an occupation with a high fraction of new work in the 1980s—are generally though of as largely unaffected by technological change. Yet in the mid-1980s, the first digital parking meter was introduced, replacing the mechanical parts with electronic components. The automation of tedious meter reading coincided with the creation of the title Parking lot signaler, suggesting that the work tasks of parking lot attendents shifted in response.

1980		1990		2000	
Top-10 Three-Digit Occupations	% New Titles	Top-10 Three-Digit Occupations	% New Titles	Top-10 Three-Digit Occupations	% 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

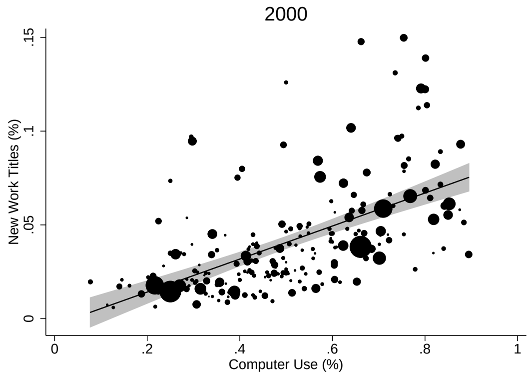
Notes: This table reports the 10 three-digit occupations with the highest fraction of new work titles appearing in each respective decade, based on data from Lin (2011). It shows, for example, that 80 percent of the job titles in the three-digit occupation Computer systems analysts and scientists in the 1991 DOT did not exist in the 1977 DOT.

Table 1: The Task Content of New Work, 1980-2000.

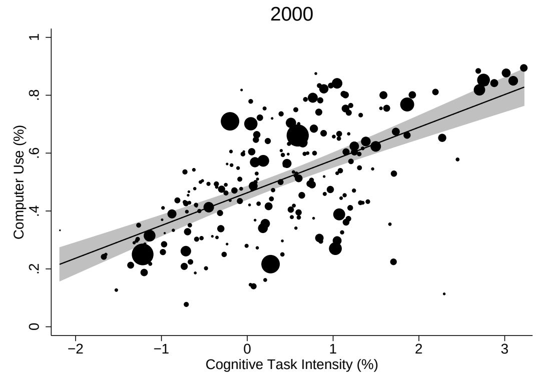
	Panel A. Occupations				Panel B. Industries			
	New Work (%)		Computer Use (%)		New Work (%)		Computer Use (%)	
	1990	2000	1990	2000	1990	2000	1990	2000
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ComputerUse_t$	0.126***	0.112**			0.096***	0.120***		
	[0.290]	[0.426]			[0.537]	[0.602]		
CTI_t			0.085***	0.094***			0.120***	0.129***
			[0.620]	[0.685]			[0.607]	[0.672]

Notes: This table reports OLS estimates of regressions on the form: $Y_i^t = \alpha + \beta X_i^t + \varepsilon_i^t$, where Y_i^t is the fraction of new occupational titles within a three-digit occupation or industry i that appeared between t and $t-10$, or the share of workers that use a computer on the job from the CPS 1989 October and 2001 September supplements. X_i^t corresponds to either the share of workers that use a computer on the job or the employment-weighted average cognitive task-intensity of an occupation or industry, calculated as in equation (1). Occupations are defined as 330 consistent three-digit occupations using the definitions in 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: *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 2: Computer Use, New Work and Cognitive Skills, 1980-2000.



(a) New Work Titles and Computer Use



(b) Computer Use and Cognitive Task Intensity

Notes: Panel A shows the relationship between the average fraction of new work titles from Lin (2011) and the percentage of workers using a computer on the job from the CPS 2001 September supplement, across three-digit industries, defined using the 1990 classifications employed by IPUMS. Panel B shows the relationship between the percentage of workers using a computer and the employment-weighted average cognitive task intensity of each three-digit industry, calculated as in equation (1). See section III.A for a more detailed description of the underlying data.

Figure 3: Computer Use, New Work and Cognitive Skills.

not in 1980. This reflects a relative decrease in routine-intensive new titles and a simultaneous increase in cognitive task-intensive occupations (panel B). Columns 4-6 reveal a similar reversal across industries, consistent with our argument that computerization is more likely to generate new work in occupations and industries that intensively rely on cognitive skills.[23] Overall, results reported in this section shed light on a previously undocumented shift in the task content of new work around 1980.[24]

III.C Measuring the Task Specialization of U.S. Cities

To measure the task specialization of U.S. cities, we combine worker-level data on occupations and location of residence from the population censuses with occupation-level data on task inputs from the 1977 edition of the DOT, to estimate the fraction of workers employed in occupations intensive in cognitive tasks for each city.[25]

We begin by calculating the cognitive task intensity of each occupation. Letting each occupation be denoted by o and each individual by i, we use data from the DOT on the input of cognitive (C_o), routine (R_o) and manual (M_o) tasks, to calculate the cognitive task intensity (CTI_o) of each occupation as:

[23] A potential shortcoming is that we do not observe the actual task content of new work, nor how the average task content per occupation of industry changes along intensive margins over time. However, under the assumption that new occupational titles are more intensive in cognitive tasks than existing titles, this would downward bias the intensity of cognitive tasks in new work after 1980.

[24] Moreover, these observed shifts in the task content of new work over time reduce concerns that new work is always more cognitive-intensive than old work, before it can be subdivided and routinized.

[25] To improve the comparability of our results with the extant literature, our approach here is similar to that of Autor and Dorn (2013). As noted below, however, using alternative approaches to estimate the task content of cities yield very similar results.

	New Work in Three-Digit Occupations			New Work in Three-Digit Industries		
	1980	1990	2000	1980	1990	2000
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Cognitive Task Intensity					
CTI_{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]
	Panel B. Cognitive, Routine and Manual Task Inputs					
$Cognitive\ Task\ Input_{t-10}$	0.008	0.032***	0.037***	0.028*	0.095***	0.086***
	[0.066]	[0.198]	[0.385]	[0.265]	[0.677]	[0.606]
$Routine\ Task\ Input_{t-10}$	0.026**	-0.001	-0.005	0.049***	-0.019	0.002
	[0.169]	[-0.006]	[-0.037]	[0.451]	[-0.131]	[0.012]
$Manual\ Task\ Input_{t-10}$	-0.001	-0.004	0.004	0.010	0.013	-0.000
	[-0.010]	[-0.055]	[0.085]	[0.223]	[0.208]	[-0.002]

Notes: This table reports OLS estimates of regressions on the form: $Y_i^t = \alpha + \beta \mathbf{X_i^{t-10}} + \varepsilon_i^t$, where Y_i^t is the fraction of new occupational titles within an occupation or industry i that appeared between t and $t-10$, $\mathbf{X_i^{t-10}}$ is a vector including either the employment-weighted average cognitive task intensity of a three-digit occupation, or industry as defined in (1), or the natural logarithm of the raw input of cognitive, routine and manual tasks. Occupations are defined as 330 consistent three-digit occupations and industries are defined according to a consistent 1990 classification scheme from 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.

Table 3: The Changing Task Content of New Work, 1970-2000.

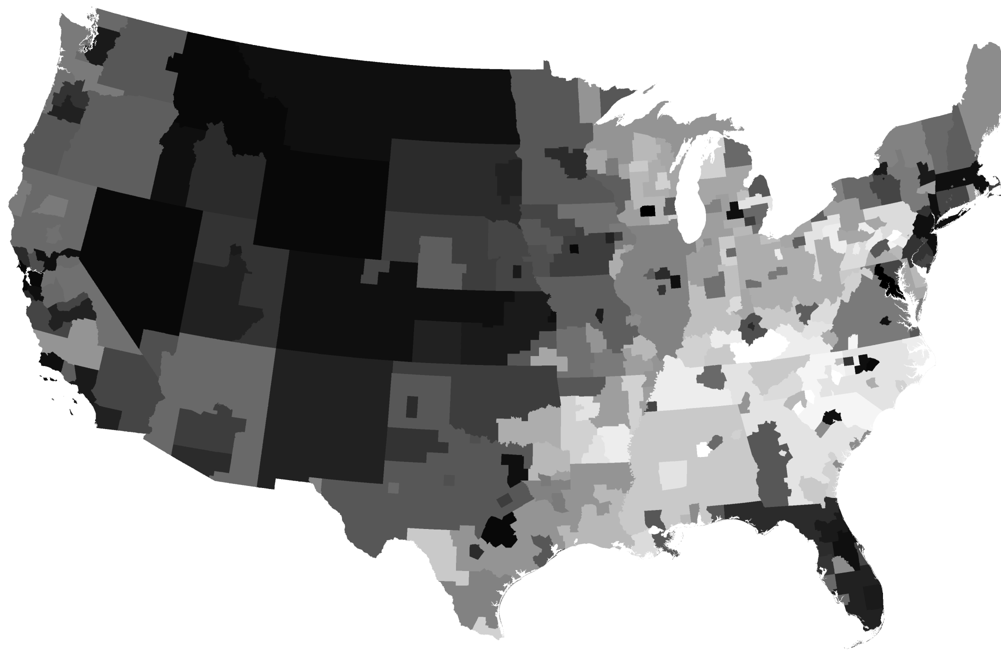
$$CTI_o = lnC_o - lnR_o - lnM_o \tag{1}$$

where CTI_o is increasing with the relative input of cognitive tasks.[26] High values of this index indicates that computer technology is likely to complement labour, whereas low values indicate a higher susceptibility to automation. Examples of occupations that are intensive in cognitive tasks are financial managers, scientists and lawyers; occupations with low cognitive task intensity are, for example, punching and stamping press operatives, dressmakers and drillers. Furthermore, we define a subset of occupations that are relatively intensive in cognitive tasks. Formally, letting Ω correspond to the 75th percentile of cognitive task intensity in 1970, weighting each occupation by its 1970 employment share, we create an indicator variable:

$$CIO_{io} = \begin{matrix} 1 & if & CTI_o > \Omega \\ 0 & if & CTI_o < \Omega \end{matrix} \tag{2}$$

taking the value 1 if a worker is employed in a cognitive task-intensive occupation (CIO_{io}) and 0 otherwise. Letting L_c denote the size of the labor force in city c, we then calculate the cognitive task specialization (CTS_c) for each city as the share of workers that are employed in occupations intensive in cognitive tasks:

[26] For the few occupations that have zero manual and cognitive inputs in the DOTs, we replace these with the 5th percentile of each task score respectively.



Notes: This map shows the cognitive task specialization of U.S. cities, shown here for CONSPUMAs using shapefiles obtained from IPUMS (https://usa.ipums.org/). The fraction of workers in occupations that are intensive in cognitive tasks is shown as increasing from light to dark hues.

Figure 4: Cognitive Task Specialization Across U.S. Cities, 1970.

$$CTS_c = \frac{\sum_{i \in c} CIO_{io}}{L_c} \tag{3}$$

In principle, there are many different ways to construct our measure of task specialization. However, below reported results are robust to various alternative cutoffs (Ω) and insensitive to many alternative ways to calculate relative task intensities (CTI_o).[27]

Figure 4 shows the cognitive task specialization of U.S. cities in 1970. Many cities with high shares of cognitive work in 1970 are also commonly associated with subsequent adaptation to computer technologies: San Francisco, the fourth most cognitive city in 1970, was also the most computer-intensive region in the country by 1990 (Doms and Lewis, 2005). Similarly, Austin—in fifth place—hosts a number of Fortune 500 tech-companies, such as Google, Intel and Texas Instruments. Finally, Madison, the most cognitive city in 1970, has the highest percentage of individuals holding Ph.Ds in the United States.[28]

[27] For instance, using other cutoffs (e.g., the median or the 80th percentile) yields very similar results. Defining the task intensity of occupations using only cognitive and routine tasks similarly does not alter any of our main findings.

[28] It is also worth noting that the relative task specialization across cities is highly persistent across decades: the raw correlation between our measure of cognitive task specialization and its decadal lag is close to 90 percent, and is highly statistically significant. This supports our view that patterns of task specialization in 1970 partly reflecting long-run differences in the tasks that were carried out in U.S. cities.

IV Task Specialization and Technological Adaptation in U.S. Cities: Empirical Evidence

In this section, we describe our empirical strategy and test our main prediction: that cities historically endowed with cognitive skills experienced differentially higher rates of technological adaptation after 1980. We further examine the extent to which such a shift is evident in population, skills supply and wages. In particular, we document that cities specialized in cognitive tasks in 1970 initially experienced slower adaptation to technological progress, whereas the very same cities experienced much faster adaptation rates after 1980. We also document simultaneous relative increases in population, college-educated workers and hourly wages.

IV.A Empirical Strategy

Consider the fraction of workers found in new work Y, in city c, in state s, in year t as determined by a time-varying factor λ_t, capturing the extent to which new technologies translate into new work titles:[29]

$$Y_{cst} = \lambda_t + \mu_{cst} \tag{4}$$

Now consider that the error term, μ_{cst}, consists of three components: $\mu_{cst} = \alpha_c + \gamma_{st} + \varepsilon_{cst}$, where α_c is a fixed city-component, γ_{st} corresponds to census-division- or state-specific shocks that vary by year, and ε_{cst} is an independently distributed random term. Here, α_c may reflect factors that are quasi-fixed at the city-level; for example, cities with historical endowments of cognitive skills may in all years be more prone to expand into new work if such skills are correlated with entrepreneurship or the propensity to innovate. Region-specific shocks, γ_{st}, such as state legislative changes or changing fortunes of regionally concentrated industries, may similarly predict the extent of technological adaptation.

If technological advances after 1980 became increasingly complementary to cognitive tasks, cities historically endowed with cognitive skills should experience differentially more rapid technological adaptation *after* 1980. In our main empirical specification, we therefore pool data over the three decades in our sample, and estimate an expanded version of equation (4):

$$Y_{cst} = \alpha_c + \gamma_{st} + \lambda_t + \delta \left(CTS_{cs}^{1970} \times \psi_t \right) + \mathbf{X}_{\mathbf{cst}}^{'} \theta + \varepsilon_{cst} \tag{5}$$

where we interact the 1970-level of cognitive task specialization (CTS_{cs}^{1970}) with a dummy (ψ_t) taking the value 1 for the period subsequent to 1980, and 0 for other periods. Our hypothesis is that, one would expect that $\delta > 0$, if technological adaptation increased differentially in cognitive cities after 1980. Additional specifications allow the effect to differ by decade, where an increasing effect over time would correspond to intensifying differences in new work over time, consistent with learning spillovers in cities that adopted new technologies early on.

[29] In practice, this factor also serves to capture the extent to which the number of new occupational titles differ between the census *Classified Indexes* and the DOTs due to methodological changes or other idiosyncrasies between the underlying data sources. For brevity, we focus the discussion on technological adaptation, although a similar estimation strategy for our other outcomes—population, human capital and wages—can be motivated analogously.

Interpreting δ in equation (5) as a causal link between cognitive skill endowments and technological adaptation relies on the identifying assumption that absent the Computer Revolution, initially cognitive cities would have developed similar to other cities after 1980. Importantly, our specification leverages cross-sectional variation in cognitive task specialization determined prior to the advent of the Computer Revolution.[30] In addition, we allow cities to develop differentially along many 1970 outcomes that may be correlated with initial task specialization. In particular, extended specifications include controls for initial manufacturing employment, the fraction of college-equivalent workers, city population and the fraction of the non-white and foreign-born population.[31] For the statistical inference, we cluster standard errors at the city-level, allowing for arbitrary patterns of heteroscedasticity and serial correlation (Bertrand *et al.*, 2004).[32]

IV.B Main Results

Table 4 reports estimates of equation (5), showing that cognitive cities experienced more rapid technological adaptation after 1980, relative to cities that specialized in routine or manual work. Based on the estimate in column 1, we calculate that a 10 percentage point increase in the cognitive task intensity of a city in 1970 (corresponding to an increase from the 25th to 75th percentile, or shifting the task composition of Pittsburgh to that of Philadelphia) is associated with a 1.6 percentage points higher fraction of the local labour force in new work (corresponding to 70 percent of standard deviation of new work across U.S. cities in the post-1980 period).[33]

To further illustrate the magnitude of our estimate, consider the cases of San Francisco and Indiana, PA, where 30 and 14 percent of the workforce did cognitive work in 1970, respectively. In 2000, 7.4 percent of San Francisco's workforce were employed in work that did not exist by the beginning of that decade, whereas the corresponding fraction was 2.7 percent for Indiana. Our estimate in column 1 implies that close to half (53 percent) of the difference in technological adaptation between San Francisco and Indiana can be explained by historical differences in skill endowments.

Conditional on city-level controls interacted with a post-1980 dummy, estimated relative differences in technological adaptation are nearly identical (column 2).[34] While the inclusion

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[30]Using variation in task specialization in 1970 allows us to disentagle whether, for example, adoption of computer technology was caused by differences in skills across cities, or whether adaptation to new technologies caused subsequent changes in the skill level of cities.

[31]We define college and high school equivalents as the share of workers, aged above 25, with at least three years of college education and a high school diploma respectively, plus one half of workers with some (1-2 years) college education. Other included controls are calculated based on data from the 1970 IPUMS sample and the U.S. Census' City and County Data Books (Haines, 2005).

[32]Bertrand *et al.* (2004) discuss problems related to statistical inference in the presence of serial correlation in specifications such as equation (5). They propose that clustering standard errors at the cross-sectional unit of observation works well, when the number of clusters exceeds 50. In practice, while clustering standard errors at the state-level typically produces slightly larger standard errors in our regressions, it does not affect our statistical inference.

[33]A substantial part of new work appeared in the agricultural sector in the 1970s, in particular related to agricultural engineering, raising concerns that our results are driven by these few occupations. However, results presented in this section and all below reported results are robust to excluding the agricultural sector from the sample.

[34]Results are very similar if we instead allow controls to vary by year. However, we prefer relying on cross-sectional variation in 1970, since many outcomes after 1980 arguably are endogenous to technological

of census division- and state-by-year fixed effects respectively decreases the estimated magnitude, there remains a large, positive and statistically significant relationship between cognitive task specialization and technological adaptation after 1980 (columns 3 and 4). When allowing differences in new work to vary by year, column 5 shows that differences intensified in magnitude through the 1980s and 1990s; testing the equality of coefficients across decades leads us to reject that they are the same (*p-value* = 0.00).

We next address some alternative mechanisms emphasized in the literature. Column 6 controls for industry variety, measured by a Hirschman-Herfindahl index.[35] Cities with a historically diverse set of industries seemingly experienced somewhat larger additions of new work after 1980, though this effect is quantitatively small and not statistically significant. Another mechanism is the endogenous adoption of new technologies based on factor prices. Although a higher relative supply of college-educated workers, or the fraction of the population with a college education, is associated with more new work after 1980, it has little effect on estimated changes in new work due to historical differences in cognitive skills.

Overall, the results presented in this section provide robust evidence that cities with historical endowments of cognitive skills experienced higher rates of technological adaptation after 1980. During a period of nation-wide gravitation toward jobs that intensively require cognitive skills, these results shed light on the substantial variation in the rate of these shifts across U.S. cities.

Robustness Our findings are robust across various specifications. Importantly, our results are not driven by a small subset of cities, by differences in worker composition, or confined to only highly skilled occupations.

City Characteristics. Although Figure 1 shows a very tight correlation between cognitive tasks and new work, one empirical concern is that our estimates are driven by a subset of cities in our sample. To alleviate such concerns, Table 5 (columns 1-10) shows that estimated changes in new work are similar inside and outside the Sunbelt, when looking outside the South, in more and less dense cities, in cities with a historically high and low fraction of college-educated workers and in cities with high and low manufacturing employment.[36] Similar magnitudes largely reduce concerns that our results are driven by a small subset of cities.

Worker Composition. To adjust for spatial sorting of workers, driven by unobserved city-level factors that may be correlated with the interaction term in equation (5), additional specifications use the probability that a worker is observed in new work, net of observable worker-level characteristics, as a dependent variable. Letting n^t_{io} denote the probability that a worker i in occupation o is to be found in work that did not exist in the census classification at the beginning of each respective decade t, we pool data on some 11 million workers and estimate regressions of the form:

$$n^t_{ic} = \alpha + \mathbf{X}^{\mathbf{t}'}_{\mathbf{ic}}\theta + \nu^t_{ic} \tag{6}$$

adaptation.

[35]This index is calculated as $HHI_{ct} = \sum_i s^2_{ict}$, where s is the share of employment in two-digit industry i in city c. We have experimented with alternative measures based on 1- and 3-digit industries, with very similar results.

[36]For simplicity, we define these cutoffs (e.g., manufacturing employment or fraction of college workers) by the median 1970 value across cities in our sample.

	New Work Titles							
	Baseline (1)	Controls (2)	CD-FE (3)	State- FE (4)	Time-Varying (5)	HHI (6)	SS (7)	CSHEQ (8)
$CTS_{1970} \times Post_{t>1980}$	0.156***	0.202***	0.173***	0.170***		0.202***	0.201***	0.140***
	(0.017)	(0.018)	(0.019)	(0.023)		(0.018)	(0.018)	(0.023)
$CTS_{1970} \times Post_{t=1990}$					0.162***			
					(0.017)			
$CTS_{1970} \times Post_{t=2000}$					0.243***			
					(0.021)			
$HHI_{1970} \times Post_{t>1980}$						0.001		
						(0.061)		
$SkillSupply_{1970} \times Post_{t>1980}$							0.000	
							(0.002)	
$CollegeShare_{1970} \times Post_{t>1980}$								0.058***
								(0.018)
Controls								
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census-by-year FE	No	No	Yes	No	No	No	No	No
State-by-year FE	No	No	No	Yes	No	No	No	No
City Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports OLS estimates of equation (4) in the main text. The left-hand side variable is the estimated fraction of workers that were employed in new work across 363 U.S. cities (N=1,089). Statistical significance based on robust standard errors clustered at the city-level is denoted by: *** p<0.01, ** p<0.05, * p<0.10.

Table 4: Task Specialization and Technological Adaptation, 1970-2000.

where $\mathbf{X}'_{\mathbf{it}}$ includes a quartic in age and dummies for non-whites, sex, marital status, 1-digit industry, and educational attainment (high school degree, some college and college degree, respectively). In a second step, we use the vector of estimates θ to predict the probability that a worker is to be found in new work $\widehat{n^t_{ic}}$. We then estimate the residual probability ν^t_i, which corresponds to the probability that a worker i is observed in new work, net of observable characteristics. Finally, we average for each city and decade, using workers' census weights. This allows us to examine additions of new work for each city, cleaned from variation that arise from compositional differences, such as demographics or industrial specialization across cities. As reported in column 11, a positive and statistically significant relationship remains between cognitive task specialization and differential technological adoption after 1980; results are similar when we restrict the sample of workers to non-migrants (column 12). Thus, workers in historically cognitive cities are more likely to transition into new work after 1980 than observationally similar workers in other cities.[37]

Occupations. Finally, we address the question of whether our results primarily reflect changes in highly skilled occupations, such as managerial jobs. To this end, columns 8-11 report relative changes in technological adaptation within major occupational categories. Importantly, higher rates of shifting workers into new work is evident within managerial, production and technical occupations. There is, however, a negative relationship within service occupations. While our general findings are therefore unlikely to mainly reflect city-level differences in occupational or functional specialization, they are consistent with evidence of employment growth in low-skill, manual service occupations, in local labor markets with high initial shares of routine employment (Autor and Dorn, 2013).

IV.C Changes in Population, Human Capital and Wages

Estimated Impacts on Population From estimating equation (5), Table 6 reports estimated changes in population, showing that historically cognitive cities experienced larger relative increases in population after 1980.

As reported in column 1, increasing the 1970 cognitive task-intensity of a city by 10 percentage points—equivalent to moving from Cleveland to San Francisco—is associated with a relative population increase of 18 percent (0.17 log points). This corresponds to more than 150 percent of the average decadal population growth over the period 1980 to 2000. Adding census division- and state-year fixed effects yields smaller relative changes in population, although they remain economically and statistically significant (columns 2 and 3).

The remaining columns of Table 6 report estimates in various subsamples: (1) for cities within and outside the Sun Belt; (2) for cities with historically high and low shares of manufacturing employment; and (3) for more and less densely populated cities. Warm and dry weather has been a key predictor of U.S. city growth over the late-20th century, evident in the rapid growth of cities such as Atlanta, Houston, Phoenix and Miami. Estimated relative increases in population are evident both within and outside the Sun Belt (columns 4 and 5), suggesting that our results are not driven by a correlation between a warm climate and historical skill endowments.[38] Similarly, estimated relative changes in city size is evident both

[37]It is important to note, however, that while this procedure allows us to gauge to what extent relative differences in technological adaptation are driven by compositional changes—for example, due to inward migration of more educated workers—it will result in a lower-bound estimate, since such changes may be endogenous to differences in technological adaptation across cities.

[38]We define the Sun Belt-states as: Alabama, Arizona, California, Florida, Georgia, Louisiana, Mississippi,

	City Characteristics										Worker Composition		Occupations			
	Sunbelt		South		Density		Skilled		Manufacturing		Worker Residual		Within Major Occupational Groups			
	Inside	Outside	Inside	Outside	High	Low	Yes	No	High	Low	All	Non-Migrants	Managers	Production	Technical	Services
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
$CTS_{1970} \times Post_{t>1980}$	0.206***	0.204***	0.198***	0.150***	0.214***	0.192***	0.163***	0.224***	0.202***	0.198***	0.070***	0.076***	0.089***	0.074***	0.110***	-0.028***
	(0.034)	(0.024)	(0.027)	(0.028)	(0.025)	(0.029)	(0.029)	(0.026)	(0.038)	(0.021)	(0.020)	(0.020)	(0.014)	(0.016)	(0.016)	(0.010)
Controls																
City & Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports OLS estimates of equation (4) in the main text. The left-hand side variable is the estimated fraction of workers that were employed in new work across 363 U.S. cities (N=1,089). Statistical significance based on robust standard errors clustered at the city-level is denoted by: *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 5: Cognitive Skills and New Work - Robustness Checks.

in a sample of cities with above- and below-median 1970 manufacturing shares (columns 6 and 7), although estimated changes are smaller and not statistically significant in the former.[39] Since our city aggregates consist of regions of differing size, one last concern is that our results are driven by more densely populated areas. Yet, estimated increases are nearly identical in densely and sparsely populated cities (columns 8 and 9).

Overall, these results assign an important role to historical task specialization in understanding patterns of urban growth following the Computer Revolution. Moreover, such an interpretation and the gist of our empirical estimates are consistent with popular perceptions of urban decline in the U.S., emphasizing the relative decline of cities such as Buffalo, Cleveland or Detroit—cities that all historically specialized in largely non-cognitive work.[40]

Estimated Impacts on Human Capital Table 7 documents that cognitive cities experienced disproportionately larger increases in college-educated workers after 1980. Shifting the cognitive task specialization of a city from the 25th to 75th percentile (roughly 10 percentage points) is associated with an increase in the share of college equivalent workers of 2.1 percentage points. Adding city-level controls and state-year fixed effects more than doubles the estimated magnitude (columns 2 and 3). Replacing the outcome with the log ratio of college to high school equivalent workers—a measure of relative skill supply—yields a similar result (column 4). Estimated increases are consistently positive and generally statistically significant also within major industries (columns 5-9).

Taken together, these results paint a clear picture of differential rates of technological adoption in U.S. cities leading to differences in the demand for skills, in turn inducing net inward migration of skilled workers. Such an interpretation is also consistent with the fact that, between 1970 and 2000, cities in the upper quartile of cognitive task specialization in 1970 (such as San Jose and Salt Lake City), increased their average share of college-equivalent workers in our sample from 25 to 45 percent; similar changes for cities in the lower quartile (such as Tuscaloosa or Racine) was 14 to 31 percent. This provides an alternative, although partly complementary, explanation to work showing that cities with a high initial density of college graduates also experienced higher rates of human capital growth over this period (Berry and Glaeser, 2005).

Estimated Impacts on Wages Figure 5 graphs the sharp reversal in relative wage growth between the 1970s and the two subsequent decades in cognitive cities, mirroring the shift in technological adaptation over the same period (see Figure 1). Accordingly, while cognitive cities experienced slower wage growth during the 1970s, wages increased more rapidly in these cities from the 1980s onwards. Such a reversal is consistent with technological change becoming increasingly complementary to cognitive skills after 1980, as documented in the previous section.[41]

Table 8 provides regression evidence to support our interpretation of these scatter plots, from estimating equation (5), replacing the left-hand side variable with average log hourly

Nevada, New Mexico, North Carolina, South Carolina and Texas.

[39]This is likely a results from the smaller variation in task specialization among cities that historically relied on manufacturing.

[40]These three cities, for example, all have below-median levels of cognitive task specialization in 1970.

[41]Moreover, since averages wages in cognitive cities were higher in 1980, the reversal in relative patterns of wage growth also resonates with the extensive literature documenting that, beginning in the 1980s, U.S. regional convergence slowed down substantially (Barro *et al.*, 1991; Glaeser and Gottlieb, 2009).

				Sample Decomposition					
	Baseline	Census-year FE	State-year FE	Sun Belt	Outside	High Mfg.	Low Mfg.	High Density	Low Density
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$CTS_{1970} \times Post_{t>1980}$	1.698***	1.244***	1.126***	2.804***	1.202***	0.311	1.174**	1.771***	1.749***
	(0.273)	(0.392)	(0.369)	(0.441)	(0.248)	(0.338)	(0.454)	(0.343)	(0.463)
Controls									
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census-by-year FE	No	Yes	No	No	No	No	No	No	No
State-by-year FE	No	No	Yes	No	No	No	No	No	No
Observations	1,452	1,452	1,452	488	964	728	724	724	728

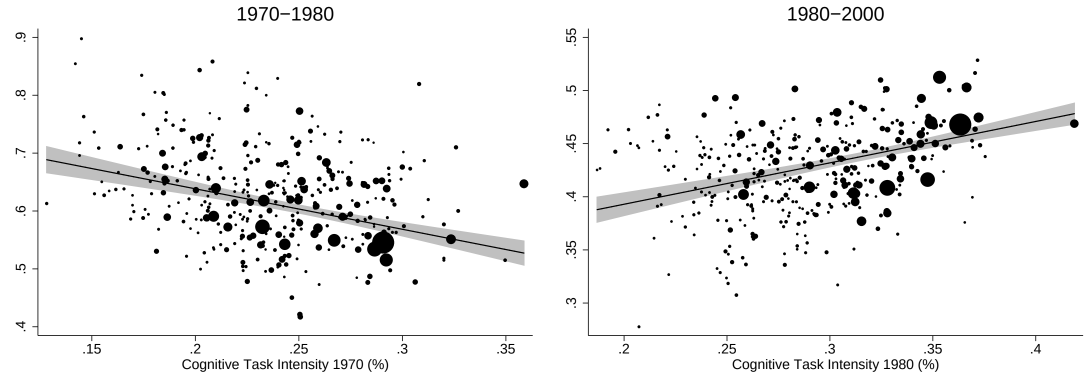
Notes: This table reports OLS estimates of equation (4) in the main text. The left-hand side variable is log city population across 363 U.S. cities (N=1,452). Statistical significance based on robust standard errors clustered at the city-level is denoted by: *** p<0.01, ** p<0.05, * p<0.10.

Table 6: Cognitive Task Specialization and Population Growth in U.S. Cities, 1970-2000.

					Sample Decomposition				
	Baseline	Controls	State-year FE	Skill supply	Prof. Services	Manufacturing	Trade	Construction	Transport
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$CTS_{1970} \times Post_{t>1980}$	0.208***	0.435***	0.436***	3.930***	0.296***	0.029	0.044**	0.048***	0.049***
	(0.049)	(0.065)	(0.076)	(0.416)	(0.054)	(0.030)	(0.020)	(0.011)	(0.012)
Controls									
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-by-year FE	No	No	Yes	Yes	No	No	No	No	No
City Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports OLS estimates of equation (4) in the main text. The left-hand side variable is the share of college-educated workers across 363 U.S. cities (N=1,452). Statistical significance based on robust standard errors clustered at the city-level is denoted by: *** p<0.01, ** p<0.05, * p<0.10.

Table 7: Cognitive Task Specialization and Human Capital in U.S. Cities, 1970-2000.



Notes: These figures show decadal changes in average log hourly wages based on IPUMS data for 363 consistently defined U.S. cities against the initial cognitive task intensity of each city. They reveal a reversal in relative patterns of wage growth in cities that were more and less specialized in cognitive work in the beginning of each respective period. See the Data Appendix for a description of the underlying data.

Figure 5: Cognitive Task Specialization and Wage Growth in U.S. Cities Before and After 1980.

wages. Following a large literature on empirical growth regressions (e.g., Durlauf *et al.*, 2005), we control for wage convergence by allowing for differential changes across cities based on their 1970 wage level in the post-1980 period.[42] Column 1 reports our baseline estimate, which implies that a 10 percentage point increase in cognitive task specialization in 1970 is associated with a 0.04 log point relative wage increase.

These estimates may partly reflect a sorting of workers into cities that are dense in tasks that are complementary to their skills. In principle, under the assumption that new work is relatively more skill-intensive than existing occupations, migrants would be expected to be positively selected from the sending populations (Borjas, 1987). To the extent that ability is captured by educational attainment, evidence presented in the previous section is consistent with such an interpretation. Net of worker-level observable demographic and educational differences, estimated changes in wages are positive and statistically significant, although smaller in magnitude (column 4). Smaller magnitudes reflect the extent to which our results are driven by compositional changes, due to the selection of skilled workers into cognitive cities, which is consistent with above reported estimates revealing simultaneous relative increases in the fraction of the workforce with a college degree over the same period. Thus, relative increases in wages does not merely reflect the fact that workers in new work are more educated than those found in old work, but is suggestive of higher rates of technological adaptation increasing wages above and beyond differences due to observable worker characteristics.

Substantial relative increases in wages are also evident within major (1-digit) industry groups (columns 5-9). This provides indirect evidence that wage gains in cognitive cities does not merely reflect shifting patterns of industry specialization.

[42]Estimating relative changes in wages without controlling for initial wage levels leads to a positive, but imprecisely estimated, coefficient on initial cognitive task specialization, due to the positive correlation between initial wages and cognitive task specialization.

					Sample Decomposition				
	Baseline	Controls	State Trends	Residual Wages	Prof. Services	Manufacturing	Trade	Construction	Transport
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$CTS_{1970} \times Post_{t>1980}$	0.361***	0.873***	0.823***	0.537***	0.567***	0.803***	0.698***	1.118***	0.118
	(0.112)	(0.160)	(0.189)	(0.148)	(0.160)	(0.232)	(0.187)	(0.283)	(0.228)
Controls									
City and year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-by-year FE	No	No	Yes	No	No	No	No	No	No
Initial wage	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports OLS estimates of equation (4) in the main text. The left-hand side variable is the average log hourly wage across 363 U.S. cities (N=1,452). Statistical significance based on robust standard errors clustered at the city-level is denoted by: *** p<0.01, ** p<0.05, * p<0.10.

Table 8: Cognitive Task Specialization and Wage Growth in U.S. Cities, 1970-2000.

V Concluding Remarks

U.S. cities have 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 historical skill endowments shaped their economic trajectories over the course of three decades. Throughout the 1970s, when technological change was biased towards routine tasks, cognitive cities experienced relatively slow technological adaptation, measured by the prevalence of new occupational titles. By contrast, in the 1980s and 1990s, cities that were intensive in cognitive skills at the dawn of the Computer Revolution, adapted faster by shifting labour into new work. Our findings thus imply that the success of a city in a traditional technology may put it at a disadvantage in adapting to the arrival of new technologies. Importantly, cities that adapted to computer technologies experienced faster growth in population, skills supply and wages—patterns that were absent in the 1970s, prior to the advent of the PC. We interpret these findings as suggesting that cognitively specialized cities were well poised to take advantage of the Computer Revolution. Such an interpretation and the gist of our empirical estimates are generally consistent with popular perceptions of urban 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. Our results do not seem to reflect differences in human capital across cities, nor cities' industrial past, pointing to task specialization as an important factor to understand urban growth dynamics.

The results presented in this paper show how rapid technological progress can erode the comparative advantages of also once highly adaptive cities. For example, having been a leading copper exporter, Detroit became a metals importer as the city ran out of ores around 1880. Yet, its highly diversified local economy—producing paints, pumps, stoves, medicines, steam generators etc.—provided the foundation for the emergence of the automotive industry a few decades later (Jacobs, 1969). More recently, however, Detroit has run out of steam, filing for Chapter 9 bankruptcy in 2013. In conjunction with such anecdotal evidence on urban obsolescence, our findings suggest that policies to support declining companies and industries are unlikely to yield sustained urban development over the long-run. Instead, we emphasize the need for cities to adapt by creating new work to address rapidly changing environments. As recent work suggests that the next generation of big data-driven technologies will benefit in particular creative and social skills, policy makers would do well in promoting investments in transferable cognitive skills that are not particular to specific businesses or industries (Frey and Osborne, 2013).

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