Technology Shocks, New Work and Urban Development: The Shifting 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 patterns of task specialization.
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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, in 1879, when George Eastman invented the emulsion-coating machine

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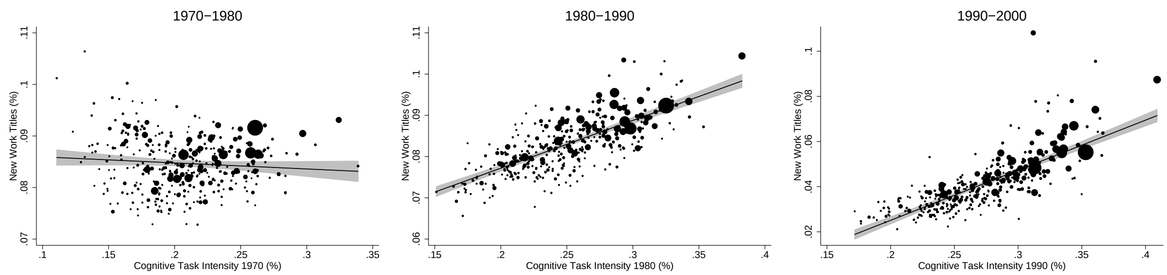
[1]Christensen (1997) shows in some detail how disruptive technologies have reshaped a wide range of industries, from computer hardware to steel manufacturing, causing leading companies to fail in the process. For example, beginning in the 1960s, the U.S. steel industry experienced a major disruption 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).



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 II.A for a more detailed description of the underlying data.

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

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 (Lucas Jr and Goh, 2009).

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 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)

[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.

Figure 1 documents the central result of our paper: a sharp reversal in the relationship between cognitive skills and the fraction of workers in new types of work across U.S. cities, coinciding with the Computer Revolution. Whereas cities dense in cognitive skills experienced slightly lower shifting of labour into new work in the 1970s, the very same cities exhibited substantially more rapid technological adaptation through the 1980s and 1990s.[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 task specialization across cities. Similar to a difference-in-differences design, our empirical strategy exploits two sources of variation: historical variation in the task specialization of cities and changes in the direction of technological change over time, plausibly exogenous to the individual city.[4] Importantly, exploiting cross-sectional variation in task specialization, prior to the Computer Revolution, and aggregate variation in technological change, limits the set of potentially confounding factors.

Our regression results reveal substantially faster technological adaptation in cities that historically specialized in cognitive tasks 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 the relative supply of skills, industry variety or historical differences in cities' reliance on manufacturing.

In tandem with higher technological adaptation after 1980, cities that historically specialized in cognitive work 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 dynamics underlying technological adaptation is important, also to understand patterns in urban development.

Our paper relates to several literatures. First, we build on a substantial body of work emphasizing technology diffusion as key to explaining income differences across and within nations (Solow, 1956; Romer, 1990; Mokyr, 1990; Comin and Mestieri, 2013). While this literature offers crucial insights to the productivity contri-

[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. In 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.

[4] We provide evidence of this technological shift associated with the Computer Revolution, by showing that new job titles increasingly appeared in occupations and industries that were more intensive in cognitive tasks after 1980.

bution of technology, it does not explain why technologies are adopted differentially. In a seminal contribution, Lin (2011) sheds some light on this, showing that new work appears in cities with a variety of industries and educated workers. We build on these findings by documenting that task specialization provides a relatively important determinant of why some cities create more new work than others, also when controlling for alternative explanations, such initial skill-abundance and industrial diversity. Furthermore, instead of focusing on cross-sectional differences in technological adaptation, we document how the appearance of new technologies have translated into shifting patterns of new work and urban development over time.

Second, a growing literature on the task content of employment examines the polarization of the U.S. labor market over recent decades, as computer technology has displaced workers from routine tasks (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 the appearance of new types of work associated with technology diffusion, rather than the distributional impact of technological change on employment between existing occupations. Importantly, we observe a shift in the technology-task complementarity of new work: while new job titles were still associated with occupations intensive in routine tasks in the 1970s, additions of new work have mainly appeared in cognitive occupations since the 1980s. Furthermore, in contrast to a subset of this literature examining the impact of firm-level computer inventories on local labor markets, we use a broader measure of technological change, allowing us to examine the relationship between cognitive skills and technological adaptation, also before the diffusion of the PC (Autor and Dorn, 2013).

Third, our results relate to work suggesting 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). This may partly be explained by differential rates of technological adaptation associated with hetrogeneity in skill abundance. For example, Beaudry *et al.* (2010) document that initially skill-adundant cities, measured by the share of college educated workers, differentially adopt computer technology. In contrast, we follow Autor and Dorn (2013), linking the concept of skill directly to job tasks in the firm, capturing also how computer technology either constitutes a complement or substitute for labour. We further add to this literature by showing how the Computer Revolution has caused growing inequality between cities, emphasizing the importance of changing complementarities of new technologies and different types of work tasks to understand the recent divergence in human capital and urban growth across the U.S.

The remainder of this paper is structured as follows. In the following section, we review the relevant literature and introduce our conceptual framework. 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.

I Background and Conceptual Framework

In this section, we provide a brief overview of recent technological advances, describing the distingushing characteristics of the Computer Revolution and its importance to the creation of new types of work. To guide our empirical analysis, we then outline a simple conceptual framework linking technological adaptation to urban development.

I.A The Computer Revolution, Task Specialization 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.[5] 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 connetcted to computers, and data entry clerks benefited from video display terminals, gradually replacing punch card data entry.

The automation of these 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. Furthemore, 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—the number of computers-in-use in the U.S. increased from 3.1 to 51.3 million between 1980 and 1990.[6] 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).[7] New technologies have however not merely shifted the composition of employment

[5]See Bresnahan (1999) for a more detailed description.

[6]See Computer Industry Almenac (1996).

[7]Accompanied by employment growth in manual service occupations, that are not amenable to computerization, these shifts are reflected in a polarization of labour markets in most developed economies (Goos and Manning, 2007; Goos *et al.*, 2009; Autor and Dorn, 2013).

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.[8] 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 leverage the cognitive skills of workers. 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.[9]

Yet, although the Computer Revolution has arrived everywhere, 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). A large literature links human capital to urban development, arguing that skills have come to dictate U.S. city fortunes (Glaeser *et al.*, 1995; Simon and Nardinelli, 1996, 2002; **?**). In particular, cities with a higher fraction of college-educated workers have experienced faster productivity growth, more entrepreneurship and faster population growth (Glaeser and Saiz, 2004; Glaeser *et al.*, 2012). Educational attainment, however, is a noisy proxy for workers' skills. To more accurately measure skills, several studies have therefore relied on occupational descriptions of the tasks performed by workers, reflecting that while skills are applied to job tasks to produce output they do not produce output *per se*.[10] Importantly, occupational descriptions can also capture the shift in the dimension along which U.S. cities specialize, from a specialization by industry to a specialization by function (Duranton and Puga, 2005).[11] In tandem with these

[8]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. Furthermore, Doms *et al.* (1997) show that plants using new technologies employ more educated workers, more managers, professionals, and precision-craft workers, and pay higher wages. However, their longitudinal analysis reveals a low correlation between skill upgrading and the adoption of new technologies.

[9]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.

[10]A task is a unit of work in the production process, whereas a skill is a worker's stock of capabilities to perform various tasks (Acemoglu and Autor, 2011). Hence, 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).

[11]In particular, improvements in transport and communication technology has made it easier for corporate leaders to remain in the cities, while shifting production to cheaper locations, contributing to increasing ge-

findings, recent work documents not only that larger cities rely more on cognitive skills (Scott, 2009; Florida *et al.*, 2012), but also that the urban wage premium partly is a premium to workers performing cognitive tasks (Bacolod *et al.*, 2009). Taken together, this possibly reflects an increasing complementarity between cognitive skills, cities and computer-related technologies over recent decades.

I.B Technological Adaptation and Urban Development: Conceptual Framework

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).[12] 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.[13] 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 work intensive in cognitive tasks corresponds to production processes that are more likely to be altered by new work, rather than job displacement. In the presence of spillovers across firms in a city, small initial differences in technological adaptation will also intensify over time.

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

ographical separation of the management and production operations of firms (Chandler, 1977). Furtermore, Michaels *et al.* (2013) document that, over the course of the twentieth century, U.S. cities have successively specialized in interactive cognitive tasks relative to rural areas—a trend that is not driven by any one industry or occupation.

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

[13] 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).

out-migration (Blanchard and Katz, 1992).[14] 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.[15] 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).[16]

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.

II Data and Measurement

In this section, we describe the data sources used to measure the task specialization of cities 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 hetrogeneity in task specialization across U.S. cities.

II.A Data Sources

To examine the relationship between task specialization, technological adaptation and urban development, we construct our dataset from primarily three sources: (1) micro-level data from the Integrated Public Use Microdata Series (IPUMS) (Ruggles *et al.*, 2010); (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)

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; 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

[14]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.

[15]More broadly, 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).

[16]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).

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 consists of a combinations of counties so that reported units exceed the confidentiality threshold. Cities are constructed by aggregating consistently defined PUMAs and county groups, to create consistently defined geographical units of observation over the period 1970-2000. 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 the period 1970-2000. 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).[17]

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.[18] New occupational titles are reported at the five- or nine-digit levels in the census *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, containing the fraction of new titles in each three-digit occupation, that appeared for the first time in the 1970s, 1980s and 1990s, respectively.[19] We match these lists to consistently defined occupations throughout 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.

While new work arises from a range of innovations, and is admittedly an imperfect measure of technological change, it has several distinct advantages for our purposes. Relative to diffusion measures of single technologies—such as imports of computer equipment or firm-level computer inventory—it allows us to examine the relationship between task specialization and technologies predating the Computer Revolution.[20] Patents are another frequently used measure of innovation, capturing a wide range

[17]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.

[18]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) and 1990s (1990-2000) throughout the paper.

[19]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.

[20]Caselli and Coleman (2001) use data on imports to study the cross-country diffusion of the computer. Beaudry *et al.* (2010) and Autor and Dorn (2013) use data on firm-level computer inventory to study the impact

of technologies. Yet, patents have well-known limitations—many important technological breakthroughs are not patented, many patents are never commercialized, and patents differ substantially in their technical and economic significance (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.[21] 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.

Job Tasks

The DOT and its successor, the Occupational Information Network (O*NET), were devised by the U.S. Employment Services to ease the matching of job applicants' skills with the production tasks of firms, with 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.[22] To reduce the dimensionality and mitigate problems of high collinearity of these task measures, we follow Autor *et al.* (2003) in using the original DOT data collapsed into three measures of broad task inputs: cognitive, routine and manual. Importantly, these three measures correspond to tasks that are either complemented by (cognitive), substituted for (routine), or 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 correspond to 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

of computers on local labor markets. Following Krueger (1993) it is also common to regress individual wages on whether a worker uses a computer or not; in response to this literature, 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."

[21] 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). Furthermore, there is often a long time-lag between the issuance of a patent and the actual implementation of the technology.

[22] 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.)

developed by Autor and Dorn (2013).

II.B The Changing Task Content of New Work: Qualitative and Regression Evidence

New work has become increasingly associated with cognitive work after 1980, suggesting that technological change has become more complementary to workers with cognitive skills, following the Computer Revolution. In this section, we show that this shift is evident within occupational titles, but also in systematic cross-occupation and cross-industry comparisons.

Table 1 lists the 10 three-digit occupations with the highest fraction of new work titles by decade. In the 1980s, we see the first computer-related occupations, and by the 1990s, virtually all top 10 occupations are directly related to computer technologies: Eight of the ten occupations with the highest fraction of new work titles—e.g., Network and computer systems administrators and Database administrators—are directly associated with the computer. 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 to 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.

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 signaller*, suggesting that the work tasks of parking lot attendents shifted in response. Overall, while these qualitative indications suggest that new occupational titles over time increasingly appeared in occupations intensive in cognitive tasks that also experienced innovations, they do not shed light on whether a systematic relationship between tasks and new job titles exists.

Table 2 reports regression results of the fraction of new work and inputs of cognitive, routine and manual tasks across three-digit occupations and industries, showing 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. To reduce the influence of occupations and industries with very low employment, all regressions are weighted by employment. Standardized coefficients are reported in brackets to ease interpretation.

Panel A, columns 1-3, shows that new occupational titles were more prevalent in occupations that were intensive in cognitive tasks in 1990 and 2000, but 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 three-digit industries, consistent with our argument that computeriza-

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 ten (three-digit) occupations with the highest fraction of new work titles appearing in each respective decade over the period 1970 through 2000, based on data from Lin (2011).

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

	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 estimates of OLS 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. Statistical significance based on robust standard errors is denoted by: *** p<0.01, ** p<0.05, * p<0.10.

Table 2: The Changing Task Content of New Work, 1970-2000.

tion is more likely to generate new work in occupations and industries that intensively rely on cognitive skills, for which computer technology provides a complement.[23] Overall, results reported in this section shed light on a previously undocumented shift in the task content of new work around 1980.[24]

II.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

[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.

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:

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

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:

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

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

Figure 2 shows the cognitive task specialization of U.S. cities in 1970. In addition, Table 3a and 3b lists the 10 cities (defined by CBSAs) with the highest and lowest cognitive task specialization in 1970, and their respective rank in terms of of new work in each subsequent decade. (Figure 1 shows the city-level correlations between task specialization and new work.) Many of the cities with high shares of cognitive work in 1970, are commonly associated with a high degree of technological adaptation since the Computer Revolution. For example, San Francisco—the fourth most cognitive city in 1970—has experienced some of the fastest implementation of new work since the 1980s, consistent with the popular perception of San Francisco as one of the leading U.S. information technology cities.[28] Similarly, Austin—in fifth place—hosts a number of Fortune 500 tech-companies, such as Google, Intel and Texas Instruments. In 2004, Madison–the most cognitive city in 1970–had the highest percentage of individuals holding Ph.Ds in the United States. Similarly, Des Moines was named the third largest "insurance capital" of the world by *Business Wire*. At the very bottom of

[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.

[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] In 1990, the San Francisco Bay Area was the most computer-intensive region in the country (Doms and Lewis, 2005).

the list are cities such as Tuscaloosa and Pottsville, that have experienced relatively poorer outcomes since the 1980s.[29]

Panel A. Most Cognitive Cities

	New Work (Rank)		
City (CBSA, state)	1970s	1980s	1990s
Madison, WI	191	19	13
Washington, DC	16	1	3
Des Moines, IA	85	88	49
San Francisco, CA	48	20	8
Austin, TX	141	25	5
Raleigh, NC	135	8	2
Spokane, WA	309	85	121
Bridgeport, CT	239	45	46
Columbia, SC	65	34	77
Reno, NV	151	284	159
Average	138	61	48

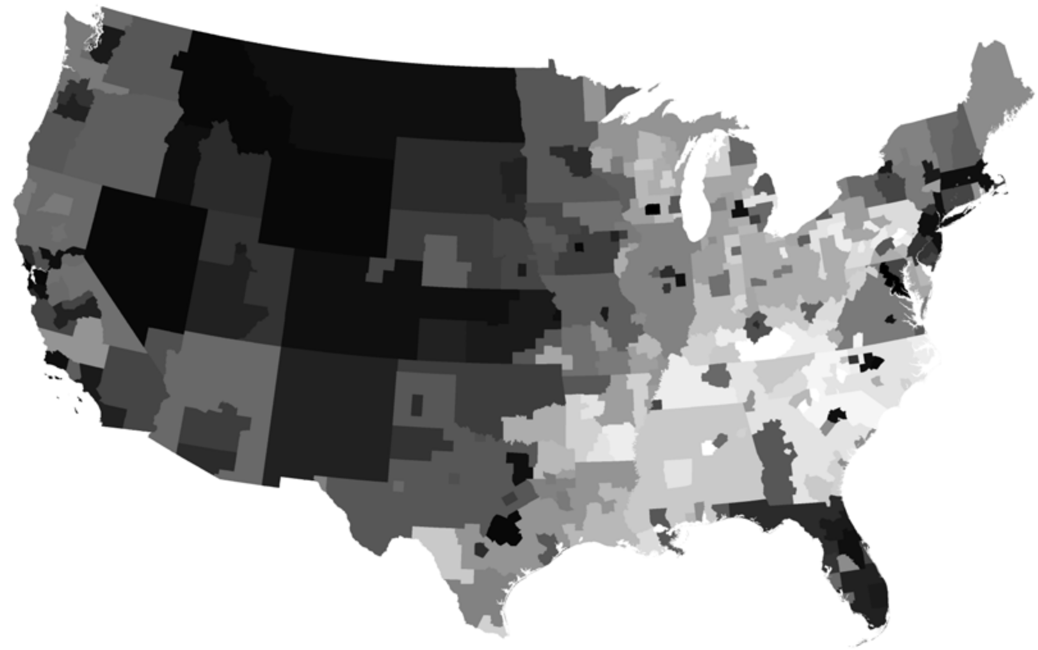
Panel B. Least Cognitive Cities

	New Work (Rank)		
City (CBSA, state)	1970s	1980s	1990s
Altoona, PA	314	221	241
Lebanon, PA	204	212	226
Hickory, NC	123	347	325
Lexington, NC	289	340	254
Spartanburg, SC	88	325	211
Anderson, SC	132	322	187
Indiana, PA	92	257	340
Tuscaloosa, AL	158	138	110
Salisbury, NC	170	311	212
Pottsville, PA	2	351	296
Average	157	282	240

Notes: This table reports respectively the ten cities with the highest (Panel A) and lowest (Panel B) fraction of workers in cognitive-task intensive occupations in 1970. As described in the main text, occupations are ranked based on relative cognitive task input from the 1977 edition of the DOTs.

Table 3: Most and Least Cognitive Cities and New Work by Decade, 1970-2000.

[29]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 reflecti long-run differences in the tasks that were carried out in U.S. cities.



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 2: Cognitive Task Specialization Across U.S. Cities, 1970.

III 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 specialized in cognitive tasks 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.

III.A Empirical Strategy

To motivate our empirical strategy and illuminate identification problems, consider first 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, corresponding to the extent to which technological change translates into new work titles:[30]

[30]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 idiosyncracies between the underlying data sources. For brevity, we focus the discussion on technological adaptation, although

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

where μ_{cst} is a random error term. Now consider that μ_{cst} additively 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 that are dense in workers with cognitive skills may in all years be more prone to expand into new work if, for example, such skills are correlated with entrepreneurship or the propensity to innovate. Region-specific shocks, γ_{st}, such as state legislative changes or shifting 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 that historically specialized in such tasks should experience differentially more rapid technological adaptation *after* 1980. In our main empirical specification, we therefore pool data on the fraction of new work 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. If technological adaptation increased differentially after 1980 in historically cognitive cities, one would expect that $\delta > 0$. Additional specifications allow the effect to differ by decade:

$$Y_{cst} = \alpha_c + \gamma_{st} + \lambda_t + \delta_1 \left(CTS_{cs}^{1970} \times \psi_{t=1990} \right) + \delta_2 \left(CTS_{cs}^{1970} \times \psi_{t=2000} \right) + \mathbf{X}_{\mathbf{cst}}^{'} \theta + \varepsilon_{cst} \tag{6}$$

where an increasing effect over time ($\delta_2 > \delta_1$) would correspond to intensifying differences in new work over time, consistent with learning spillovers in cities that adopted new technologies early on, lowering costs for subsequent adoptes.

Interpreting δ in equation (5) as a causal link between cognitive task specialization and technological adaptation relies on the identifying assumption that, absent of the Computer Revolution, cities that were initially specialized in cognitive tasks would have developed in a similar way as other cities after 1980. Importantly, our specification leverages cross-sectional variation in cognitive task specialization in 1970, plausibly reflecting historical differences in the tasks that are carried out within cities, determined prior to the advent of the Computer Revolution.[31] While this identifying assumption is arguably strong, 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

a similar estimation strategy for our other outcomes—population, human capital and wages—can be motivated analogously.

[31] Using varition 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.

fraction of college-equivalent workers, city population and the fraction of the non-white and foreign-born population.[32] 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).[33]

Addressing Worker Selection 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 replace the outcome variable with the probability that a worker is observed in new work, net of observable worker-level characteristics. Letting n_{io}^{t} 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 draw upon data on more than 11 million individual workers and estimate regressions of the form:

$$n_{ic}^{t} = \alpha + \mathbf{X_{ic}^{t\prime}}\theta + \nu_{ic}^{t} \tag{7}$$

where $\mathbf{X_{it}^{\prime}}$ 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 $\widehat{n_{ic}^{t}}$ to estimate the residual probability ν_{i}^{t}, which we then average for each city and decade, weighted by workers' census weights. Additional specifications use a sample of workers restricted to those that did not migrate within the previous 5-year period. These procedures eliminate variation in new work that may be driven by variation in demographics or industrial specialization across cities.[34]

III.B Main Results: Task Specialization and Technological Adaptation

We begin by documenting the correlation between task specialization and new work across 363 U.S. cities, over the period 1970 to 2000. Specifically, Table 4, panel A, reports results from regressing new work on cognitive task specialization in 1970, as well as by the beginning of each decade. (Each cell corresponds to a separate regression.) Panels B and C report similar regressions, including state and census division fixed effects respectively. Consistent across all specifications, there is a slightly negative relationship between cognitive task specialization and technological adaptation

[32] 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).

[33] 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.

[34] 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.

in the 1970s, that turns positive and statistically significant in the two subsequent decades.[35]

	1980	1990	2000
	(1)	(2)	(3)
Panel A. Across Cities			
CTS_{1970}	-0.012	0.104***	0.185***
	(0.008)	(0.008)	(0.017)
CTS_{t-10}	-0.012	0.116***	0.222***
	(0.008)	(0.006)	(0.012)
Panel B. Within Census Divisions			
CTS_{1970}	-0.001	0.114***	0.203***
	(0.008)	(0.008)	(0.019)
CTS_{t-10}	-0.001	0.121***	0.220***
	(0.008)	(0.006)	(0.012)
Panel C. Within States			
CTS_{1970}	-0.001	0.131***	0.256***
	(0.009)	(0.009)	(0.022)
CTS_{t-10}	-0.001	0.126***	0.234***
	(0.009)	(0.006)	(0.013)

Notes: This table reports estimates from regressing the fraction of workers in new work in 363 consistently defined U.S. cities on the fraction of workers employed in occupations intensive in cognitive tasks in 1970, and the beginning of each decade respectively; each cell corresponds to a separate regression. 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 New Work, 1970-2000.

Table 5 reports estimates of equation (5), showing that cognitive cities—cities historically specializing in cognitive work—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).

To further illustrate the magnitude of our estimate, consider the case 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

[35] 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.

	New Work Titles							New Work Titles within Major Occ. Groups			
	Baseline	Controls	CD-FE	State- FE	Time-Varying	Residual	Residual (Non-migrants)	Managers	Production	Technical	Services
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$CTS_{1970} \times Post_{t>1980}$	0.156***	0.202***	0.173***	0.170***		0.070***	0.076***	0.089***	0.074***	0.110***	-0.028***
	(0.017)	(0.018)	(0.019)	(0.023)		(0.020)	(0.020)	(0.014)	(0.016)	(0.016)	(0.010)
$CTS_{1970} \times Post_{t=1990}$					0.162***						
					(0.017)						
$CTS_{1970} \times Post_{t=2000}$					0.243***						
					(0.021)						
Controls											
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census-by-year FE	No	No	Yes	No	No	No	No	No	No	No	No
State-by-year FE	No	No	No	Yes	No	No	No	No	No	No	No
City Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No

Notes: This table reports estimates of equation (5). The left-hand side variable is the estimated fraction of workers that were employed in new work at the city-level (N=1,089). Columns 5-8 report estimates in samples decomposed into major occupational groups, denoted in the top row (Managerial and professional specialty occupations; Precision production, craft, and repair occupations; Technical, sales, and administrative support occupations; Service occupations). 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: Task Specialization and Technological Adaptation, 1970-2000.

and Indiana can be explained by historical differences in task specialization.

Conditional on city-level controls (population, relative skill supply and demographics) interacted with a post-1980 dummy, estimated relative differences in technological adaptation are nearly identical (column 2).[36] While the inclusion 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 ($F-stat=37.5$).

One empirical concern is that these results are partly induced by the selection of workers into new work. To test if observationally identical workers are more likely to transition into new work in historically cognitive cities, we replace the outcome variable with the probability that a worker selects into new work, net of observable characteristics. As reported in column 6, 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 7). Thus, workers in historically cognitive cities are more likely to transition into new work than observationally similar workers in other cities after 1980.

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).

Overall, the results presented in this section provide robust evidence that relative to U.S. cities that historically specialized in routine and manual work, city-level specialization in cognitive work is associated with higher rates of technological adoption after 1980. During a period of nation-wide gravitation toward jobs that intensively require cognitive skills, these results further shed light on the substantial variation in the rate of technological adaptation across U.S. cities.

III.C Additional Results: 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

[36]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 adaptation.

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 subsamples restricted in three dimensions: (i) within and outside the Sun Belt; (ii) in cities with historically high and low shares of manufacturing employment; and (iii) in 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, as 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 patterns of task specialization.[37] Similarly, estimated relative changes in city size is evident both 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.[38] Since our city aggregates consists 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 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 have specialized in largely non-cognitive work.[39]

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 supply of skills—yields a similar result (column 4). Estimated increases are always 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

[37]We define the Sun Belt-states as: Alabama, Arizona, California, Florida, Georgia, Louisiana, Mississippi, Nevada, New Mexico, North Carolina, South Carolina and Texas.

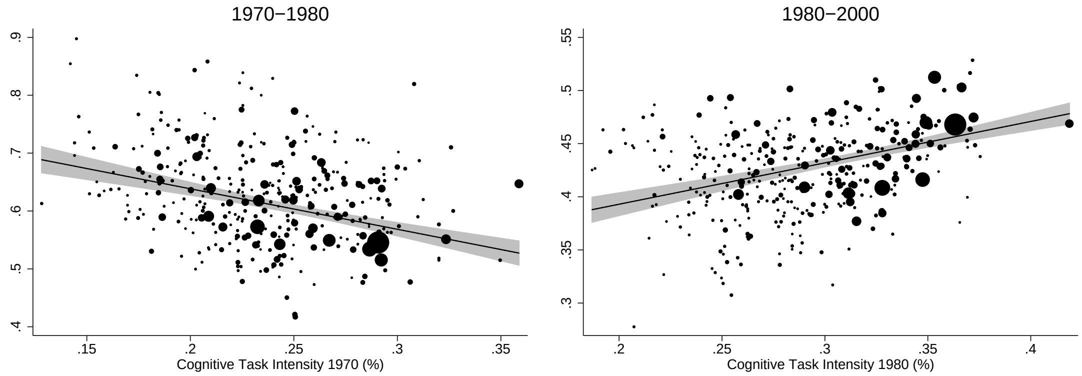
[38]This is likely a results from the smaller variation in task specialization among cities that historically relied on manufacturing.

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

				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: Notes: This table reports estimates of equation (5). The left-hand side variable is log city population.

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



Notes: These figures show decadal changes in log hourly wages for 363 consistently defined U.S. cities. 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 3: Cognitive Task Specialization and Wage Growth in U.S. Cities Before and After 1980.

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 3 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). In the 1970s, wages grew at a slower pace in cities that by the beginning of that decade specialized in cognitive work. However, between 1980 and 2000, wages increased more rapidly in the very same cities. Such a reversal is consistent with technological change becoming increasingly complementary to cognitive work after 1980, as documented in the previous section.[40]

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 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.[41] 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

[40]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).

[41]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-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: Notes: This table reports estimates of equation (5). The left-hand side variable is the share of college educated workers (N=1,452).

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

be expected to be positively selected from the sending populations (Borjas, 1987). To the extent that ability is captured by educational attainment, results 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 that reveal 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 gains in cities that historically specialized in cognitive tasks does not merely reflect shifting patterns of industry specialization.

IV Concluding Remarks

U.S. cities have fared very differently over recent decades. In this paper, we show that different patters in urban development can be explained by differental rates of adaptation to an economy-wide technology shock—the Computer Revolution. Our main piece of evidence supporting this view, is that cities historically specializing in cognitive work initially experienced slower adaptation to technological progress. Beginning in the 1980s, however, the very same cities experienced much faster adaptation rates. Our analysis thus reveals a break in the relationship between cognitive task specialization and technological adaptation. This shift also reflected in simultaneous relative increases in population, human capital and wage growth. We interpret this finding as cities historically specialized in cognitive work benefiting disproportionally from the cognitive work-technology complementarity of computer capital. 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 largely non-cognitive 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 conjuction with such anecdotal evidence on urban obsolence, our findings suggest that policies to support declining companies and industries are unlikely to yield sus-

					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: Notes: This table reports estimates of equation (5). The left-hand side variable is the log hourly wage (N=1,452).

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

tained 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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