Industrial Renewal in the 21st Century:

Evidence from U.S. Cities*

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Abstract

Where and why do new industries emerge? Using revisions of official industrial classifications, a central contribution of this paper is to document the fraction of workers in entirely new industries, stemming directly from technological change of the 2000s. Our findings speak to a growing concern about the U.S. economy's capacity to create new work: we show that in 2010 only 0.5 percent of the U.S. labour force worked in industries that did not exist a decade ago. When examining the determinants of employment in new industries across U.S. cities, we document that new industries emerge in places that are plentiful in skilled workers. IV estimates that exploit the location of land-grant colleges, opened in the nineteenth century, as an instrument for contemporary human capital assigns a causal interpretation to these results.
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I Introduction

Economists have long warned of the dynamic failure to produce new industries as old ones are being eroded. Joseph Schumpeter (1939) argued that progress occurs via structural change, Alvin Hansen (1939) predicted secular stagnation as a result of declining technological dynamism in the United States, and Charles Kindleberger (1961) concluded that long-run economic growth entails the eclipse of mature by new industries.[1] In particular, Jane Jacobs (1969) famously suggested that:

> "Our remote ancestors did not expand their economies much by simply doing more of what they had already been doing [. . .] They expanded their economies by adding new kinds of work. So do we."

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[1] In essence, Hansen (1939) argued that "when a revolutionary new industry reaches maturity and ceases to grow [. . .] as all industries finally must, the whole economy must experience a profound stagnation [...] And when giant new industries have spent their force, it may take a long time before something else of equal magnitude emerges."

While technological change has reduced the demand for labour in many old industries, only some places have successfully adapted by creating new kinds of work. In this paper, we document where new industries emerge, analyze the characteristics of the workers they employ, and examine the determinants of new industry creation across U.S. cities. Using revisions of the U.S. Census Bureau's *Alphabetical Index of Industries*, including some 22,000 industry titles used to classify respondents industry, we systematically capture new industries that appeared for the first time between 2000 and 2010. Taking advantage of detailed classification documentation, we isolate new industries that emerged as a result of new technologies becoming available.

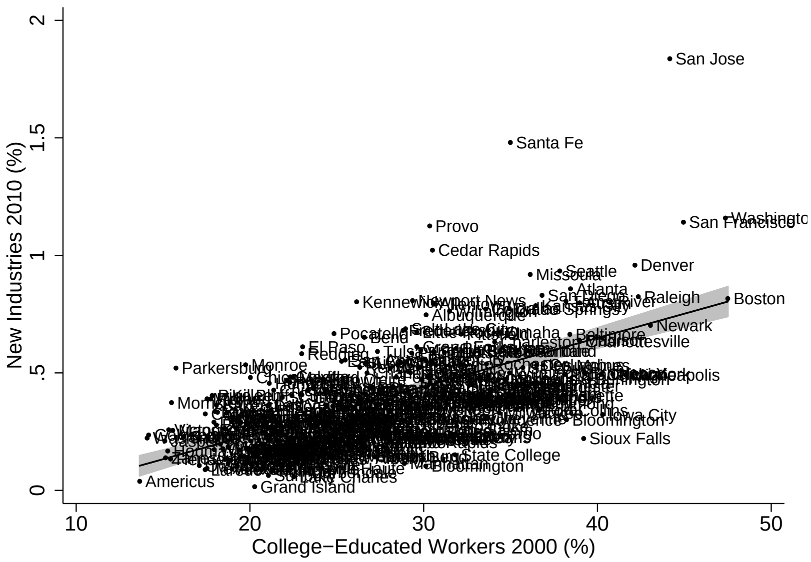
Our paper builds on a growing body of work showing that new industries cluster to benefit from knowledge spillovers (Duranton and Puga, 2001; Desmet and Rossi-Hansberg, 2009). This is nicely illustrated by the story of Silicon Valley, where frequent job-hopping has facilitated the reallocation of skilled workers towards firms with the most promising innovations (Saxenian, 1996; Fallick *et al.*, 2006).[2] Only a year after William Shockley founded Shockley Semiconductor Laboratory in 1956, several engineers left the company to form Fairchild Semiconductor, of which two would go on to found Intel. In the same way, the abundance and adaptability of educated workers has recently attracted a new generation of leading companies, spurring the creation of entirely new industries: Google, Facebook, eBay, LinkedIn, Bloom Energy and Tesla Motors, are all based in Silicon Valley.

Because skilled workers are better able to adapt to technological change (Glaeser and Saiz, 2004), and places that are plentiful in educated people benefit from the diffusion of technological knowledge across companies and industries, the simple intuition underpinning our analysis is that new industries are more likely to emerge in skilled cities. Figure 1 shows the central result of our paper: a strong positive link between the fraction of college-educated workers in 2000 and the share of workers in industries that were created between 2000 and 2010, across U.S. cities. We note that the highest fraction of workers in new industries can be found in San Jose, followed by Santa Fe, San Francisco and Washington DC.

In our empirical analysis, we use data on 1.2 million workers from the 2010 American Community Survey (ACS), allowing us to examine the characteristics of workers selecting into new industries. Workers in new industries are relatively young and better educated, implying skill-biased technological change over the period 2000 to 2010. Furthermore, for any given level of education, workers with a science, technology, engineering or mathematics (STEM) degree are more likely to select into new work. By contrast, workers with professional degrees are less likely to be observed in new industries, possibly reflecting that new work requires adaptable cognitive abilities rather than job-specific skills.

The magnitude of new job creation is however strikingly small: we estimate that in 2010, about 0.5 percent of the U.S. workforce was employed in industries that did not exist a decade ago. This finding speaks to a growing concern about the U.S. economy's capacity to create new work, stemming from a general downward trend in job creation rates over recent decades (Decker *et al.*, 2014). Nevertheless, there is a substantial variation in the share of workers in new industries across cities (see Figure 1): in San Jose, about 1.8 percent of workers are employed in new work, but only 0.2

[2] Furthermore, Zucker *et al.* (1998) show that the entry decisions of new biotechnology firms in a city depends on the existing stock of human capital in terms of outstanding scientists, measured by the number of relevant academic publications.



Notes: This figure shows the percentage of workers in 2010 that were employed in industries that were created between 2000 and 2010 and the percentage of each city's workers with a bachelor's degree or higher in 2000, across 321 U.S. cities. See the main text for a discussion of the underlying data.

Figure 1: New Industry Creation and Human Capital Across U.S. Cities.

percent in Grand Rapids.

To examine the causal link between human capital abundance and new industry creation, we use an instrumental variable (IV) strategy. Specifically, we exploit the location of land-grant colleges, established by the federal Morrill Act of 1862, as an instrument for differences in contemporary human capital. Since these institutions were established some 150 years ago, and supported by federal grants that were not allocated based on economic considerations (Edmond, 1978; Nevins, 1962; Moretti, 2004; Williams, 2010; Liu, 2013), the presence of a land-grant college is unlikely to affect the creation of new industries in the 2000s, other than by raising local human capital levels.[3] Our regression results reveal remarkable persistence in agglomeration patterns: nineteenth century land-grant colleges explain a substantial share of the geographical variation in human capital across U.S. cities in the twenty-first century, and thus indirectly spatial differences in the creation of new industries.

Our study is related to several literatures. First, we add to a series of papers showing that education is a key predictor of city growth (Glaeser *et al.*, 1995; Rauch, 1993; Simon and Nardinelli, 2002; Glaeser and Saiz, 2004; Shapiro, 2006), and a subset of this literature documenting a divergence in human capital levels across U.S. cities over the post-war period. In the model of Berry and Glaeser (2005), for example, this divergence stems from the tendency of skilled entrepreneurs to innovate in ways that create employment opportunities for more skilled workers.[4] We provide an empirical counterpart to this prediction, showing that new industries mainly emerge in skilled cities, and that skilled workers are more likely to be observed in new work.

[3]Nevertheless, in our analysis, we condition on many outcomes today, such as the local presence of universities.

[4]Furthermore, they find that the divergence of skill levels is associated with the decline in income convergence across cities. See also Barro and Sala-i Martin (1991).

Second, our findings are related to a vast literature on skill-biased technological change, showing that almost all industries began employing more educated workers during the 1970s and the 1980s (Berman *et al.*, 1994; Autor *et al.*, 1998; Machin and Van Reenen, 1998). Nevertheless, Beaudry *et al.* (2013) document a decline in the demand for skill within existing occupations and industries over the past decade, implying a reversal in the direction of technological change. By contrast, when examining workers in new industries, stemming directly from the arrival of new technologies, we find evidence of skill-biased technological change throughout the 2000s: workers in new industries are substantially better educated and earn more than twice the U.S. median wage. Because only a fraction of workers are employed in new industries, however, the impact of technological change on the aggregate demand for skills is likely to be negligible.

Third, we advance the literature examining the spatial determinants of entrepreneurship and innovation (Doms *et al.*, 2010; Glaeser *et al.*, 2010; Audretsch and Feldman, 1996; Zucker *et al.*, 1998). Relative to this literature, we focus on the determinants of industrial renewal. Thus, for our purposes, a drawback with standard measurements of entrepreneurship, such as start-ups and firm size, is that they are not indicators of structural change—i.e., they do not capture whether a company is in an old or new industry. Furthermore, unlike studies using innovation indicators, such as patents or R&D expenditure, we are able to track the extent to which the arrival of new technologies create employment opportunities in new industries.

The remainder of this paper is structured as follows. In section 2, we discuss our data, examine the characteristics of workers in new industries, and their geographical location. Section 3 examines the determinants of new industry creation across U.S. cities. Finally, in section 4, we derive some conclusions and implications for policy.

II New Industries in the 21st Century

In this section, we describe our data sources and examine the characteristics of workers employed in new industries. We further explore the geographical concentration of new industries across the United States.

II.A Data Sources and Measurement

II.A Alphabetic Index of Industries

To systematically capture the appearance of new industries, we compare the 2000 and 2010 editions of the *Alphabetic Index of Industries*, constructed by the U.S. Census Bureau to classify a respondents industry as reported in demographic surveys. Crucially, each index lists industry titles reported in earlier censuses and surveys as well as new titles reflecting the emergence of new industries in the economy.[5]

We begin by performing a string match between each of the 22,187 titles in the 2010 edition, and the 22,020 titles listed in 2000, which yields 283 nine-digit titles that did not exist a decade ago. From this list, we exclude (1) All public industries (e.g. the Department of Homeland Security); (2) Not specified titles (e.g. Automotive any other–See "Auto"); (3) Individual companies that have a corresponding industry

[5] However, some titles are not listed immediately because they are too new to be included in the indexes, or rarely used.

title (e.g. we excluded eBay but kept Internet auction sites). Furthermore, in a later robustness check we also excluded all duplicates (e.g. we kept Internet auction sites but excluded Auction sites, internet). Because duplicates also exist among old titles, however, we kept all new duplicates in our main sample. This decision reflects the assumption that duplicates exist randomly and thus equally for old and new titles.

We note that new industry titles may emerge for various reasons. To capture industries resulting from technological change we perform a manual review of the remaining titles, categorizing them according to the underlying reason for their emergence. First, a concern is that new titles are the result of reclassifications or splitting of existing industries. We therefore proceed by manually screening each title in 2010 that did not match with a 2000 title, comparing them to all 2000 titles within the corresponding three-digit industry. Second, some new titles stem from import substitution. For example, while yam production has been a core industry in Nigeria for decades, it only emerged as a sufficiently significant industry in the U.S. to constitute a title in 2010. Third, some titles are the result of privatization efforts: we find private prisons among new industries. Fourth, new titles may simply reflect changing consumer preferences or shifts in demand.[6] Finally, and most importantly, new industries emerge as a result of technological change. Titles including Wind farms, Biotechnology food research, and Space vehicle research, all stem from technological progress. Furthermore, Internet news publishers, Social Networking Service and Video and Audio Streaming intuitively correspond to new industries arising from the advent of the World Wide Web in the 1990s.

Using the above described classification approach, we develop a novel measurement of industrial renewal, including 71 entirely new industry titles directly associated with new technologies becoming available. Doing so, we advance the existing literature defining new industries as the entry of established industries that did not previously exist in a region or city, which may simply reflect life-cycle patterns of industry diffusion (Duranton and Puga, 2001; Duranton, 2007; Neffke *et al.*, 2011), or long-run trends in the concentration of industrial activity (Kim, 1995).[7]

New industry titles also have several advantages to other measurements of technological change. Patents, for example, have well-known limitations: many technologies are not patented and only some patents end up being used in production (Griliches, 1990).[8] Other studies have thus used product and occupational classifications to track the spatial implementation of new technologies. For example, Bahar *et al.* (2012) examine the entry of new products to countries export portfolios as a measure of technology diffusion. Moreover, Lin (2011) meticulously compared changes in the census occupational classifications to identify new work resulting from technological change. Relative to these measurements, new industry titles have the advantage of corresponding more closely to the introduction of new products and services in the economy, while capturing the extent to which a wide range of technologies create employment opportunities in new industries.

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[6] The first flea markets in the United States, for example, date back to the Monday Trade Days in Canton, Texas, which began in 1873. More recently, as flea markets have become increasingly popular, they received an industry title in 2010.

[7] Furthermore, to capture industrial renewal, other studies examine employment shares in existing high-tech sectors, showing that tech-jobs have expanded the most in skill abundant places (Fallah *et al.*, 2014).

[8] 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. Other 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).

We collapse our final sample of 71 nine-digit titles to the three-digit industry level reported in the 2000 (5%) Census and 2010 ACS microdata samples (Ruggles *et al.*, 2010), allowing us to match our detailed industry data with worker-level samples from the IPUMS.[9] We restricted our analysis to individuals aged 18 to 65, outside of Alaska and Hawaii, that do not live in group quarters, and with industry responses that we are able to match with data from the *Alphabetic Index of Industries*. These restrictions result in a sample of about 1.2 million workers.

Furthermore, we assign our micro-level data to consistent cities. Doing so, we use CZ boundaries, reflecting geographical areas in which people live and work, as defined by Tolbert and Sizer (1996). Specifically, CZs constitute counties with strong commuting links, which were identified based on county-level commuting data from the 1990 Census.[10] Using the crosswalk from Autor and Dorn (2013), we collapse our microdata to 722 CZs, of which 321 constitute urban areas.[11] We refer to these urban CZs as cities throughout the paper.

II.B Examples of New Industries

In 2010, we estimate that 0.5 percent of U.S. workers were employed in industries that did not exist by the turn of the century.[12] In practice, as it is likely that new industry titles initially contain less employment within detailed industries than old ones, there are reasons to believe that this estimate is upward biased. To put this number in perspective, Decker *et al.* (2014) shows that during the years before the Great Recession, U.S. job creation rates averaged 15.8 percent, while job destruction rates had fallen to 13.4 percent. Our findings thus suggest that the creation of new industries only explains a small fraction of total job reallocation.

Table 1 shows examples of industries that underwent significant restructuring throughout the 2000s. Internet publishing and broadcasting, Electronic auctions, and Computer systems design exhibit among the highest fractions of new titles in our sample: in the Electronic auctions industry, for example, close to 67 percent of all industry titles appeared for the first time between 2000 and 2010. While these industries employ only a fraction of the U.S. workforce (ranging from 0.01 to 1.33 percent), they are substantially more skill-intensive than other industries: the share of workers with a college degree in these industries ranges from 69.9 to 51.9 percent, relative to our sample average of 28 percent. Furthermore, workers in industries that experienced rapid technological change earn much higher wages. The average wage for workers in industries with fractions of new titles in our sample is 67,146 USD—that is, more than twice the U.S. median wage in 2010.

Taken together, these results are consistent with a vast literature suggesting that technological advances over recent decades have favored more skilled workers and are

[9] For each industry title, the 2010 Alphabetical Index of Industries also report 2010 Census Industry Codes, which makes it straightforward to match new industry titles to their corresponding detailed industries in the Census and ACS samples.

[10] We use the 1990 definition of CZs because some of our controls are based on data that maps to this definition. Differences between the 1990 and 2000 CZ definitions are, however, marginal.

[11] There are 741 U.S. CZs, but our sample is reduced since we exclude Alaska and Hawaii.

[12] This estimate relies on the assumption that workers are evenly distributed across titles within detailed industries and is calculated for workers that conform to the mentioned sample restrictions (see section II.A.2). Furthermore, as we exclude agriculture and mining industries in all our calculations our estimate is inevitably upward biased.

suggestive of a substantial wage premium for workers that select into newly created industries.[13]

II.C Characteristics of Workers in New Industries

In this section, we examine the characteristics of individuals that predict employment in new industries. Specifically, we estimate regressions of the following form:

$$NI_i = \alpha + \mathbf{X_i} + \varepsilon_i \tag{1}$$

where NI_i is the probability that a worker is employed in a new industry and $\mathbf{X_i}$ includes a number of individual characteristics.

Table 2 shows that education is a quantitatively important predictor of workers shifting into new industries: the estimates in column 1 implies that a worker with a bachelor's degree is 0.50 percentage points more likely to be employed in a new industry, relative to a worker without any degree. An exception is workers with professional degrees, which are on average less likely to be observed in new industries. Although we are unable to disentangle the mechanisms underlying these results, this may reflect that most professional degrees—for example, architects or dentists—are associated with industries that have changed little over recent decades. An alternative interpretation is that new work requires cognitive adaptability, rather than specific skills.

Column 2 explores the role of different types of skills, as reflected in workers field of degree. For any given level of education, workers with a STEM degree are more likely to select into new industries.[14] Furthermore, workers in new industries are on average relatively young and typically male: female workers are less likely to be observed in new work.[15]

It is of course possible that if more educated workers seek out sectors of the economy that are more skill-intensive, such as professional services, and these sectors simultaneously experience higher additions of new industry titles, this correlation may drive these results. It is therefore reassuring that when we look only at selection into new industries within major (1-digit) industry groups, we find similar results (column 3).

II.D The Geography of New Industries

Figure 2 maps the fraction of workers in new industries across the 722 CZs of the conterminous United States. We note that new industries are especially prevalent in the Western U.S., in particular in California, and along the northeastern coast. By contrast, the appearance of new industries is lower on average in the Midwest and within the Rust Belt. Furthermore, there is substantial variation in new industry creation across

[13] To evaluate if these wage gains are simply the effect of higher average education in these industries, we estimate wage regressions for the 1.2 million workers in the 2010 ACS sample, controlling for demographic and educational characteristics. In such regressions, the fraction of new industry titles, in the industry that a worker is employed, is a significant and positive predictor of a worker's wage. Lin (2011) observes a similar premium for workers employed in new occupations in the 1980s and 1990s, arguing that such wage premium may reflect the inherent risk with the experimentation of new technologies in the labor market. An alternative, or complementary, explanation is that the observed wage premia may reflect a selection (on unobservable factors) of the most able workers into new types of industries.

[14] We define a degree within the following fields as belonging to STEM: Communication Technologies; Computer and Information Sciences; Engineering; Engineering Technologies; Biology and Life Sciences; Mathematics and Statistics; Military Technologies; Nuclear, Industrial Radiology, and Biological Technologies; Transportation Sciences and Technologies.

[15] Finally, we note that the married and Asian population is particularly prominent in new industries.

Industry (3-digit code) (1)	New Industries (%) (2)	% of U.S. Empl. (3)	College (%) (4)	Avg. Wage ($) (5)	Examples of New Titles (6)
Internet publishing and broadcasting and web search portals (6672)	85.7%	0.06%	69.6%	$81138	Internet video broadcast sites Social Networking Service Internet game sites
Electronic auctions (5591)	66.6%	0.01%	52.2%	$47257	Internet auction sites
Computer systems design and related services (7380)	7.1%	1.34%	69.9%	$80324	Computer programming service Logistics services Web page designing, exc. internet
Avg. Across U.S. Industries	1.27%	-	28.6%	$44333	-

Notes: This table presents examples of detailed industries (column 1) that experienced large additions of new industry titles (column 2, with examples in column 6), identified from a comparison of the 2000 and 2010 editions of the U.S. Census Bureau's *Alphabetical Index of Industries*. Industry characteristics are calculated from the 2010 ACS sample, for employed and non-institutionalized workers, aged 18-65 (armed forces, agricultural, mining and public industries are excluded). College shares (column 4) are calculated as the percentage of workers, aged above 25, with a bachelor's, master's, professional or doctoral degree. Average wages are based on an arithmetic average of yearly wages (column 5).

Table 1: Examples of New Industries, 2000-2010.

	Outcome: Probability that Worker is Employed in a New Industry		
	(1)	(2)	(3)
Bachelor's Degree (=1)	0.499***	0.383***	0.053***
	(0.013)	(0.014)	(0.013)
Masters Degree (=1)	0.536***	0.414***	0.233***
	(0.019)	(0.019)	(0.018)
Professional Degree (=1)	-0.058***	-0.226***	-0.433***
	(0.022)	(0.024)	(0.023)
Ph.D. (=1)	0.728***	0.549***	0.579***
	(0.039)	(0.040)	(0.036)
STEM Field (=1)		0.485***	0.597***
		(0.022)	(0.019)
Age	-0.004***	-0.004***	-0.002***
	(0.000)	(0.000)	(0.000)
Female (=1)	-0.225***	-0.213***	-0.074***
	(0.008)	(0.008)	(0.009)
Married (=1)	0.044***	0.038***	0.082***
	(0.009)	(0.009)	(0.008)
Asian (=1)	0.458***	0.402***	0.368***
	(0.025)	(0.025)	(0.021)
Black (=1)	0.040***	0.038***	0.034***
	(0.014)	(0.014)	(0.012)
Industry Controls?	No	No	Yes
Observations	1,174,972	1,174,972	1,174,972
R-squared	0.006	0.007	0.228

Notes: This table presents OLS estimates from regressing the probability that a worker is employed in a new industry on a number of individual characteristics based on the 2010 ACS sample, including employed and non-institutionalized workers, aged 18-65 (armed forces, agricultural, mining and public industries were excluded). Column 3 adds a full set of major industry fixed effects. Statistical significance based on robust standard errors clustered at the state-level is denoted by: *** p<0.01, ** p<0.05, * p<0.10.

Table 2: Characteristics of Workers in New Industries, 2010.

the Sun Belt. While few new industries have emerged in the South, the Southwest exhibits relatively high fractions of new industries. The geography of new industries thus resembles the spatial appearance of new occupations throughout the 1990s (Lin, 2011) as well as historical skill endowments across U.S. cities and regions (Berger and Frey, 2014).

Table 3 shows the cities with the highest and lowest fractions of new industries. Crucially, we find the leading cities in new industry creation to be geographically dispersed, across both states and regions. Many of the places with the highest fraction of new industries are however well-known for their specialization in information technology (Gerst *et al.*, 2009). New industries are particularly prevalent in San Jose and Santa Fe, incorporating Silicon Valley and the Info Mesa cluster respectively (also see Figure 1). The continuous industrial renewal of these clusters is well documented in the literature. Having specialized in semiconductors, Silicon Valley became a pio-

City	% Employment in New Industries
San Jose	1.83
Santa Fe	1.48
Washington, D.C.	1.16
San Francisco	1.14
Provo	1.12

Notes: This table shows the five cities with the highest fraction of employment in new industries in 2010.

Table 3: Cities with Most New Industries, 2010.

neer of the Networking equipment industry in 1984 when Leonard Bosack and Sandy Lerner founded Cisco Systems, and has since attracted a wide range of companies associated with the digital revolution, including Google, Facebook and eBay. Furthermore, the origins of the Info Mesa cluster goes back to the Los Alamos National Laboratory, established in 1943 to coordinate the Manhattan Project—the Allied programme to develop the first nuclear weapons. Today, the Info Mesa is mainly associated with software development in the field of informatics.

Other cities exhibiting relatively high fractions of new industries in the 2000s include San Francisco, Washington DC and Provo. The gist of our findings are thus consistent with popular perceptions of technological dynamism in the Bay area: Instagram, Dropbox, Uber, Internet Archieve and Twitter are all located or began in San Francisco.[16] Furthermore, the high fraction of new industries in Washington DC speaks to the growing attention received by the capitals start-up scene. According to PwC, for example, Washington DC is now among the top 5 most active U.S. cities for investment capital. Finally, Provo hosts companies such as Novell, often seen as instrumental in making the Utah Valley an important place for software development.

III The Determinants of New Industry Creation

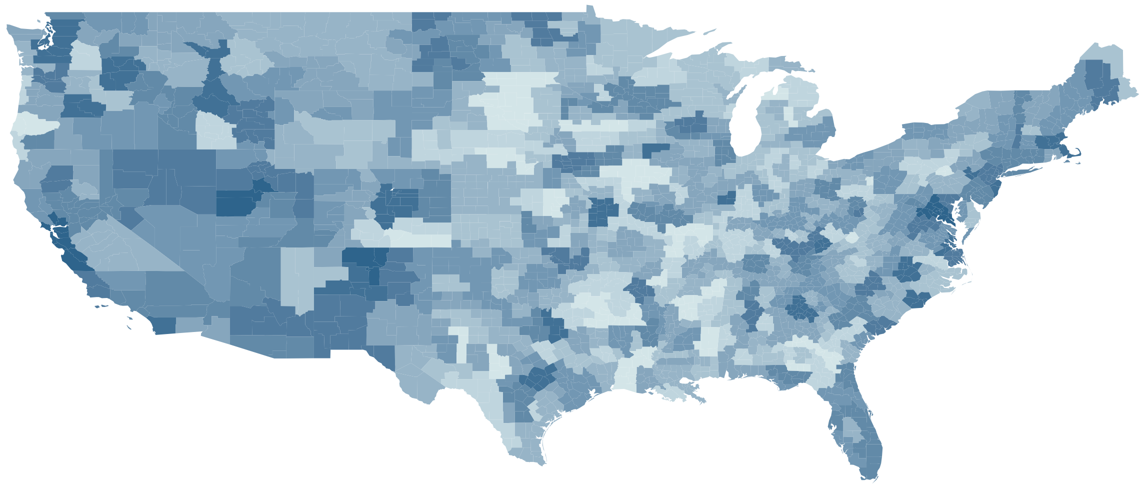
This section examines the determinants of new industry creation across U.S. cities. In particular, we outline our main hypothesis and empirical strategy, exploiting the location of nineteenth century land-grant colleges. Finally, we describe our main results.

III.A Framework

Skilled workers are more adaptable to technological change (Glaeser and Saiz, 2004). They are better at implementing new ideas, adopt new technologies faster (Bartel and Lichtenberg, 1987; Skinner and Staiger, 2005; Beaudry *et al.*, 2010), and are more likely to reallocate to the firms with the most promising innovations (Saxenian, 1996; Fallick *et al.*, 2006). Furthermore, consistent with the evidence presented above (see section II.C), showing that educated workers are more likely to shift into new industries, skilled workers are also more frequently observed in new types of occupations (Lin, 2011; Berger and Frey, 2014).

Cities that are plentiful in educated people will thus benefit from the diffusion of technological knowledge across companies and industries, as the concentration of

[16] Furthermore, already in 1990, San Francisco was the most computer-intensive place in the United States (Doms and Lewis, 2005).



Notes: This figure shows the 2010 share of workers in industries that did not exist in 2000, for the 722 CZs of the conterminous United States. Darker shades correspond to a higher fraction of workers in new industries.

Figure 2: The Geography of New Industries, 2010.

skilled workers helps productivity by easing the diffusion of new ideas.[17] Because the economic benefits of knowledge flows increase with the level of education in a city (Fagerberg *et al.*, 2012), and new industries cluster to benefit from knowledge spillovers (Duranton and Puga, 2001; Desmet and Rossi-Hansberg, 2009), we predict that the technological dynamism of a city is a function of its abundance of skilled workers.

Specifically, there are two possible mechanisms underlying the link between human capital abundance and new industry creation.[18] The first we refer to as the "innovation hypothesis", implying that the emergence of new industries is a result of skilled cities exhibiting higher rates of local innovation. For example, patterns in patenting rates suggest that skilled cities are more innovative (Carlino *et al.*, 2005), and there is evidence of entrepreneurship benefiting from a better educated local population (Doms *et al.*, 2010). The second mechanism resonates with the "reinvention hypothesis" of Glaeser and Saiz (2004), suggesting that skilled cities are more prone to adopt new technologies and reinvent themselves, without necessarily experiencing higher rates of local innovation. Instead, this hypothesis emphasizes the relevance of adoption spillovers as firms experiment with implementing new technologies, in turn reducing the costs associated with technology adoption (Griliches, 1957; Goolsbee and Klenow, 2002).[19]

[17] See Duranton and Puga (2004) and Rosenthal and Strange (2004) for an overview.

[18] A third, and complementary, explanation is that the lower relative price of skill in human capital abundant places may encourage the adoption of skill-biased technologies (Beaudry *et al.*, 2010).

[19] Over the last century, cities with more human capital have indeed grown faster relative to less skilled cities, lending support to the idea that an abundance of skills help cities reinvent themselves through adaptation to new technologies (see Glaeser *et al.*, 1995; Simon and Nardinelli, 1996, 2002; Henderson and Black, 1999; Glaeser *et al.*, 2012). Glaeser and Saiz (2004), for example, show that historical manufacturing cities with many skilled workers more rapidly shifted out of manufacturing to other industries than cities with less human capital.

In our empirical analysis, we shed some light on the relative importance of these mechanisms. We next turn to test our main prediction: that new industries mainly appear in skilled cities.

III.B Empirical Specifications

To examine the determinants of new industry creation across U.S. cities, we estimate OLS regressions of the following form:

$$NI_{cs} = \alpha + \delta C_{cs} + \mathbf{Z_{cs}}\theta + \varepsilon_{cs} \tag{2}$$

where *NI* denotes the percentage of workers in city c, in state s, that are employed in industries that appeared for the first time between 2000 and 2010. C is the fraction of the workforce with at least a bachelor's degree in 2000, and $\mathbf{Z}$ is a vector of controls.

One concern is that the concentration of skills reflect some other underlying factor, leading to omitted variable bias in our regressions, in which case the correlation between local skills and the creation of new industries may be spurious. We address such concerns in three ways. First, we include a number of city characteristics in $\mathbf{Z}$ to control for potentially omitted variables. Our city controls include: log population, labor force participation, average household income, and the fraction of the population that is black.[20] Additional specifications also introduce a set of university controls as well as variables indicating a city's reliance on manufacturing.

Our second approach consists of replacing the outcome variable with the residual from our individual-level regression of the probability of being employed in a new industry. This allows us to examine differences in new industry creation across cities, net of observable worker characteristics. In practice, this entails estimating:

$$n_{ics} = \alpha + \mathbf{X}^{\prime}_{\mathbf{ics}}\theta + \nu_{ics} \tag{3}$$

where n_{ics} corresponds to the probability that a worker i is observed in employment in a new industry and $\mathbf{X}^{\prime}_{\mathbf{it}}$ includes age and its square, as well as dummies for Asians, blacks, sex, marital status, a full set of 16 major industry fixed effects, and educational attainment.[21] In a second step, we use the vector of estimates θ to predict the probability of a worker being employed in a new industry $\widehat{n^t_{ic}}$. We then estimate the residual probability $\widehat{\nu_{ics}}$, which corresponds to the probability that a worker i is observed in new work, net of observable individual characteristics. Furthermore, we average for each city and decade, using workers census weights. This allows us to examine additions of new industries for each city, net of variation that arises from compositional differences, such as demographics, industrial specialization or the spatial sorting of workers across cities.

III.B IV Strategy: 1862 Land-Grant Colleges

Our IV strategy exploits the location of land-grant colleges, established in the nineteenth century, as an exogenous source of variation in human capital levels across

[20] These controls are calculated for each CZ based on the 2000 Census and were obtained from Chetty *et al.* (2014).

[21] Educational attainment constitutes a dummy for bachelor's degree, masters degree, professional degree, Ph.D. and whether the degree is in a STEM field.

U.S. cities.[22] These colleges were established following the federal Morrill Acts of 1862—the first major U.S. federal programme to support higher education—which donated public land to the states, intended to raise endowments for the establishment of college institutions.

Although a complex set of factors determined the location of each individual land-grant institution, there is little evidence to suggest that their location was determined by economic considerations, with many colleges established in rural areas (Nevins, 1962; Edmond, 1978; Williams, 2010; Liu, 2013). Moreover, because the land-grant program was federal, introduced more than a century ago, and focused on agricultural and mechanical arts, it is unlikely that their location affects the creation of new industries other than through higher contemporary human capital levels. However, the exclusion restriction may be violated if the presence of a university affects the creation of new industries through other channels than education, such as interactions between local firms and university staff, or research spillovers. To mitigate this concern, we condition on modern measures of university presence, so that for the exclusion restriction to hold it only requires that the location of land-grant institutions is uncorrelated with any omitted variable conditional on these controls.

In practice, we create our instrument by georeferencing maps documenting the precise location of the 1862 land-grant institutions from the U.S. Department of Agriculture, National Institute of Food and Agriculture (Figure 3 maps these land-grant institutions).[23] Using GIS software we then calculate the distance to the nearest land-grant college for each U.S. county, averaging the distance across counties located within the same CZ. To further reduce state-wide differences in the distance to land-grant institutions, we always include a set of state fixed effects in our estimates.

III.C Main Results

Table 4 presents our main results, from estimating equation (2), showing that between 2000 and 2010, employment in new industries expanded more in cities with an abundance of college educated workers.

Column 1 shows the bivariate correlation between the share of the workforce with a bachelor's degree or higher in 2000, and the fraction of workers employed in new industries by 2010 in each city. The human capital coefficient implies that a one standard deviation increase in local human capital levels is associated with 0.67 standard deviation increase in the share of workers employed in new industries.[24] A full set of state fixed effects, capturing differences in climate and other amenities, does not affect the magnitude of our estimates (column 2).

Variation in human capital levels between cities may partly reflect the presence of universities, which in itself may affect differences in the creation of new industries through, for example, research spillovers (Andersson *et al.*, 2009). Column 3 adds controls for the number of colleges and average graduation rates in each city (IPEDS 2000, 2009).[25] Although the presence of universities is positively related to the ap-

[22] Moretti (2004) uses a similar instrument to study the extent of human capital spillovers. Also see Liu (2013) who examines the historical impact of the land-grant institutions on manufacturing activity and population.

[23] Maps are available at: http://www.csrees.usda.gov/qlinks/partners/state_partners.html

[24] Estimating the same regression as in column 1, using each city's population in 2000 as weights yields an estimate of 2.60 (s.e. = 0.42).

[25] More precisely, we include controls for the number of Title IV, degree offering institutions per capita, and the income-adjusted college graduation rate, based on Chetty *et al.* (2014).

pearance of new industries, it leaves the link between local human capital and new industry creation largely unaffected.[26]

To distinguish between the two potential explanations for the link between human capital abundance outlined in section 3.2, column 4 controls for the count of utility patents per capita in each city, granted by the USPTO between 2000 and 2010.[27] Indeed, we find that more innovative cities, as captured by higher rates of patenting, are better at creating employment in new industries. Nevertheless, the link between human capital and new industry creation remains, although the magnitude is slightly reduced. While this is not to be viewed as conclusive evidence, our results support an interpretation of new industry creation being primarily driven by skilled workers implementing new technologies rather than necessarily inventing them.

	Outcome: % of CZ Employment in New Industries				
	(1)	(2)	(3)	(4)	(5)
% with College Degree	0.023***	0.022***	0.018***	0.015***	0.020***
	(0.002)	(0.004)	(0.004)	(0.003)	(0.005)
Patents, 2000-2010 (ln)				0.041**	
				(0.017)	
Number of Colleges					1.967***
					(0.592)
Graduation Rate					-0.247*
					(0.128)
City Characteristics?	No	Yes	Yes	Yes	Yes
State FE?	No	No	Yes	Yes	Yes
Observations	321	321	321	320	316
R-squared	0.412	0.430	0.597	0.616	0.620

Notes: This table presents OLS estimates of equation (2), where the outcome is the percentage of each city's workers that are employed in industries that appeared for the first time between 2000 and 2010. All explanatory variables are measured in 2000, if not otherwise noted in the table. Statistical significance based on robust standard errors clustered at the state-level is denoted by: *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 4: New Industry Creation and Human Capital Across U.S. Cities, 2000-2010.

Table 5 shows the results from estimating equation (3), where we replace the left-hand side variable with the residual from an individual-level regression, estimating the probability of being observed in a new industry on worker characteristics and a set of industry dummies. Again, this allows us to examine whether the probability that a worker living in a skilled city will transition into a new industry is higher, relative to an observationally similar worker living in a less skilled city. Controlling for worker characteristics in the first stage reduces the magnitude of our estimate, although a

[26]Similarly, Fallah *et al.* (2014) looks at differences in high-tech employment growth across U.S. counties and find no evidence that proximity to universities, including the land-grant institutions, boosts growth. Similarly, Faggian and McCann (2009) show that the key channel through which universities promote regional innovation is by raising the human capital of the local workforce, rather than localized spillovers.

[27]Data is available at: http://www.uspto.gov/web/offices/ac/ido/oeip/taf/countyall/usa_county_gd.htm. To match this county-level data to CZs, we use the crosswalk available from USDA.

positive and statistically relationship persists between city-level skills and the creation of new industries (columns 1 and 2).

Taken together, our results provide robust evidence that new industries appear in cities that are dense in skills. While our findings support the view that new industries partly reflect differences in innovation across cities, the main mechanism that underlies this relationship seems to be that an abundance of skilled workers facilitates a city's adaptation to the arrival of new technologies.

Robustness Table 7 (see Appendix) provides additional robustness checks of our main results. Column 1 shows that our results are similar when we include all 722 CZs, covering also the rural United States. Similarly, excluding Santa Fe and San Jose, with substantially higher employment in new industries relative to other comparable cities (see Figure 1), does not alter the interpretation of our results, although the estimated magnitudes are slightly reduced.

Another concern is that a historical dependence on manufacturing may have caused some cities to lose their ability to reinvent themselves. Column 4 controls for the share of employed workers, 16 years and older, working in manufacturing in 2000 and exposure to Chinese imports during the 1990s from Autor *et al.* (2013). We note that our findings are robust also to this specification.

Finally, our results are not sensitive to using alternative definitions of new industry titles (column 3 excludes all "duplicate" titles).[28] Even when including all 283 nine-digit titles from our string match, that did not correspond directly to a 2000 title, our key findings remain.

III.C IV Results

Table 6 reports our 2SLS estimates from using each city's distance to the nearest 1862 land-grant college in the first stage. Panel A documents the first stage relationship, showing that a larger share of the workforce in cities closer to a historical land-grant college had a college degree in 2010.

Panel B reports the second stage results. When comparing the results reported in Table 6 (columns 1 and 2) with their respective OLS estimates (reported in the first two columns of Table 4) it becomes clear that these are very similar. Column 3 directly controls for the fact that cities located close to historical land-grant colleges also are more likely to have closer geographical proximity to a university today, by including controls for the number of colleges per capita; the mean in-state tuition and fees for first-time, full-time undergraduates; and the income-adjusted college graduation rate (IPEDS 2000, 2009). Finally, using variation in employment net of observable worker characteristics (column 4) yields estimates that are larger compared to our OLS regressions (see Table 5, column 2). This suggests that the link between new industry creation and local human capital, shown in Figure 1, is in actual fact even stronger than implied by our OLS estimates.

[28]For example, "Auction sites, internet" and "Internet auction sites" both appeared for the first time between 2000 and 2010 in the *Index*. In this regression we exclude, for example, "Auction sites, internet" but remove "Internet auction sites."

	Outcome: Residual Employment in New Industries	
	(1)	(2)
% with College Degree	0.008***	0.008**
	(0.002)	(0.003)
City Characteristics	No	Yes
Observations	321	321
R-squared	0.355	0.394

Notes: This table presents OLS estimates of equation (2), where the outcome corresponds to the averaged residuals from individual-level regressions of the probability of employment in a new industry on demographic, educational and industry controls. All explanatory variables are measured in 2000, if not otherwise noted in the table. Statistical significance based on robust standard errors clustered at the state-level is denoted by: *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 5: Main Results

	(1)	(2)	(3)	(4)
Panel A. First Stage (Outcome: % with College Degree)				
Distance to Land Grant College (km)	-1.409***	-1.055***	-0.987***	-0.987***
	(0.436)	(0.357)	(0.336)	(0.336)
Panel B. Second Stage (Outcome: % Outcome: % of CZ Employment in New Industries)				
% with College Degree	0.022***	0.022**	0.034**	0.028**
	(0.008)	(0.011)	(0.015)	(0.013)
City Characteristics	No	Yes	Yes	Yes
University Controls	No	No	Yes	Yes
Observations	321	321	316	316
Kleibergen-Paap F-stat	10.445	8.714	4.881	4.881

Notes: This table presents OLS/2SLS estimates similar to equation (2). In the first stage, we document the negative relationship between distance to the 1862 land-grant colleges and the percentage of the labor force with a college degree in 2000 (panel A). In the second stage, we use this source of variation of skilled workers today to predict the creation of new industries between 2000 and 2010 (panel B). Statistical significance based on robust standard errors clustered at the state-level is denoted by: *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 6: IV Results

IV Conclusions: Cities and the Creation of New Industries

Historically, revolutionary technologies like the railroad, the telephone and the automobile have created vast employment opportunities in entirely new industries. Over recent decades, however, the U.S. economy has witnessed a decline in indicators of technological dynamism, such as start-ups and job reallocation, contributing to a growing concern about its capacity to create new work as old industries mature and decline (Decker *et al.*, 2014). Yet, while such indicators are informative, they do not directly capture whether jobs and companies are created as a result of new technologies becoming available.

Drawing upon original survey data, a central contribution of this paper is to document employment opportunities created in entirely new industries—that appeared for the first time between 2000 and 2010—associated with the arrival of new technologies. First, we exploit this data to examine the characteristics of workers in new industries. Our regression results are suggestive of skill-biased technological change throughout the 2000s: workers in new industries are relatively educated and earn more than twice the U.S. median wage. Furthermore, workers with STEM degrees are more likely to select into new work, while individuals with professional degrees are less likely to be observed in new industries. We interpret these findings as reflecting that new work requires adaptable cognitive abilities rather than job-specific skills.

Second, we examine the determinants of new industry creation across U.S. cities. Doing so, we document a causal relationship between initial human capital abundance and the appearance of new industries. To establish causality, we exploit the location of nineteenth century land-grant colleges, as an instrument for differences in contemporary human capital abundance. Our regression results reveal remarkable persistence in agglomeration patterns: nineteenth century land-grant colleges explain a substantial share of the geographical variation in human capital levels in the twenty-first century, and thus indirectly the fraction of new industries across cities. These findings are consistent with the model of Berry and Glaeser (2005), providing an explanation for the divergence in human capital levels across cities over the post-war period: a tendency of skilled entrepreneurs to innovate in ways that create employment opportunities for more skilled workers.

Finally, the magnitude of workers shifting into new industries is strikingly small: only 0.5 percent of the U.S. labour force are in work that did not exist in 2000. This finding resonates with concerns about the future of employment, leading prominent economists to speculate about an era of secular stagnation—an idea introduced by Alvin Hansen (1939) during the Great Depression.[29] While the overall U.S. economy has exhibited a downward trend in new start-ups and job creation for decades, even the high-tech sector started to decline in the post-2000 period, experiencing a shift in economic activity, away from young to more mature firms (Haltiwanger *et al.*, 2014). One interpretation of this decline is offered by the life-cycle pattern of the computer revolution. As investment in computer and information processing equipment surged throughout the 1980s and 1990s, a wide range of new computer-related occupations were created (Lin, 2011; Berger and Frey, 2014). Beyond the peak investment stage in 2000, however, the U.S. economy experienced a decline in the demand for new work relative to the early stages of the computer revolution (Beaudry *et al.*, 2013).

[29] See, for example, Summers (2014) and Gordon (2014).

Crucially, we find that many new industries of the 2000s stem from the advent of the World Wide Web and the following digital revolution, including Online auctions, Internet news publishers, Social networking services and the Video and audio streaming industry. Relative to major corporations of the early computer revolution, the companies leading the digital revolution have created few employment opportunities: while IBM and Dell still employed 431,212 and 108,800 workers respectively, Facebook's headcount reached only 7,185 in 2013. Furthermore, according to our estimates, online auctions—a new industry of the 2000s—employed around 0.01 percent of the U.S. workforce in 2010. Because digital businesses require only limited capital investment, employment opportunities created by technological change may continue to stagnate as the U.S. economy is becoming increasingly digitized. How firms are responding to digital technologies becoming available is a line of inquiry that deserves further attention.

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A Appendix: Additional Figures and Results

Source: http://www.csrees.usda.gov/qlinks/partners/state_partners.html

Figure 3: Land Grant Colleges, 1862 and 1890.

	Outcome: % of CZ Employment in New Industries				
	(1)	(2)	(3)	(4)	(5)
% with College Degree	0.016***	0.019***	0.018***	0.025***	0.018***
	(0.003)	(0.002)	(0.005)	(0.009)	(0.003)
City Characteristics?	Yes	Yes	Yes	Yes	Yes
Observations	722	319	321	321	321
R-squared	0.247	0.419	0.597	0.125	0.471

Notes: This table presents various robustness checks of the results presented in Table 4 in the main text. Column 1 includes all rural CZs, in addition to the 321 urban CZs. Column 2 excludes San Jose and Santa Fe from the sample. Column 3 adds controls for the fraction of employment in manufacturing and the exposure to Chinese imports during the 1990s. Columns 4 and 5 uses alternative definitions of new industries, explained in further detail in the main text. Statistical significance based on robust standard errors clustered at the state-level is denoted by: *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 7: Robustness Checks