Emerging and Disappearing Work, Thriving and Declining Firms

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Abstract

Using the text of vacancy postings from 1940 to 2000, we examine the characteristics of firms which hire for newly emerging and soon-to-be disappearing work practices. To do so, we classify job titles as emerging or disappearing according to the years in which they appear. We verify that emerging work involves higher skill levels and is closer to the technological frontier — qualities inherent to innovation. We find that, among the set of publicly listed firms, those which post ads for emerging work tend to be younger, more R&D intensive, and have higher future sales growth. Among privately held firms, those which post ads for emerging work are more likely to go public in the future. We then explore heterogeneity in the job vintage-firm performance relationship according to jobs that are in product-related technical fields versus in business related non-technical fields. New technological work correlates with R&D intensity and future sales growth, while survival and publicly traded status is more closely related to having newer vintages of business-related non-technological jobs. Our measures of firm innovativeness can be constructed for all employers, and are not limited to publicly traded firms or to industries in which R&D spending and patenting are prevalent.

1 Introduction

Firms differ markedly in their ability and inclination to innovate. The choice of whether to innovate at all, to what degree, and on what margins depends on a variety of factors.

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Firms entering a new product market segment may choose to innovate heavily on the product margin, competing to construct the most technically effective solution. Conversely, firms operating in established product markets may focus on innovating at the process and organizational margins to increase efficiencies in scalability and distribution, so as to establish market dominance. Intuitively, it seems natural that profit maximizing firms will always innovate on at least one margin to ensure their survival in the face of competition, new and old. And yet, there is significant variation in the extent, intensity, and types of innovation.

An extensive literature explores this variation in innovative activity. A common theme within this literature is that firms are resource constrained and must choose among investment in new and uncertain technological innovations ("product innovations"), improvements in existing production processes ("process innovations"), and enhancements to the business aspects of the firm ("organizational innovations") (Abernathy and Utterback, 1978; Henderson and Clark, 1990; Klepper, 1996). Some firms may choose not to innovate at all when the expected return to doing so is low (Henderson, 1995; Adner and Snow, 2010). By investing in product-enhancing technological innovations, firms trade off future profits expected from the new product against the current costs incurred towards innovating. In contrast, the benefits from process and organizational innovations materialize more quickly (Helfat and Winter, 2011; Leonard-Barton, 1992). Furthermore, the firm must have the necessary complementary capabilities to successfully integrate and profit from the new technology (Cohen and Levinthal, 1990), and must also face a customer base that values these product enhancements (Adner and Levinthal, 2001). So, there are multiple margins on which firms can innovate, if they choose to innovate at all. However, because it is so difficult to measure innovation and technology adoption in a comprehensive, comparable manner across firms and industries, empirically identifying the importance of these different margins remains a challenge.

In this paper, we use *job titles vintages*, a generally applicable and easily observed measure to infer innovative activity. Job titles characterize the types of technologies and sets of production processes used in the workplace. To give one example, in the mid-twentieth century American offices routinely employed typewriters, comptometers, and punched-card equipment.[1] In decades since, these devices have been replaced by personal computers, word processing software, and mathematical software. Mirroring these trends in technology replacement, jobs titles like *Comptometer Operator*, *Typist,* and *Stenographer* were among the most common in the 1950s and 60s but have since disappeared. Job title shifts reflect not only new technologies but also changes in the organization of production. Reflecting a broad centralization of corporate activity and an increasingly complex set of decisions

[1] Comptometers are devices capable of adding and subtracting, but not multiplying or dividing.

confronting managers (see Chandler (1990)), job titles emphasizing human resource activities — including *Human Resource Assistant* and *Human Resource Manager* — emerged only in the latter decades of the twentieth century. On the other hand, concomitant to an increase in firm scope, salespeople specialized in a single product (e.g., *Fluorescent Salesperson*) disappeared in the second half of the twentieth century.[2]

These anecdotes illustrate that the introduction of new technologies and the evolution of organizational norms manifest in the set of jobs in which individuals work. However, not all firms simultaneously adopt the same set of technologies and organizational practices. And so, the set of job titles for which firms search differ as well. When firms hire, they conduct deliberate searches for workers who will best leverage their other resources. Firms which search for workers with newly emerging job titles are conveying their intent to innovate — be it in producing or adopting a new technology, or in implementing a new organizational strategy.

Using our set of measurements on the emergence and disappearance of job titles, we study how firms actively seeking to hire workers in newer versus older vintage job titles perform. Specifically, we measure the emergence and disappearance of job titles between 1940 and 2000, drawing on text of the *Boston Globe, New York Times,* and *Wall Street Journal*. Our main hypothesis is that firms that post ads for newer vintage job titles have other characteristics reflecting innovative activity. To develop this hypothesis, we elicit other information from the text of each ad: We construct measures of the job's education requirements, as well as the technologies workers are expected to use when employed. In this sense, we are able to identify the combination of skills an employer or firm is seeking to acquire and the technologies these skills complement. Finally, for a subset of the job ads, we can identify the posted salary as well as the firm or employment agency who posted the vacancy.

Our measure, based on the vintages of job titles corresponding to each firm, complements existing measures of invention and innovation. First, a distinct advantage of our job title-based measure is that it is broadly applicable for all employers. This is in contrast to other, more conventional measures of innovative activity — e.g., R&D spending, patenting and patent citations (Cohen and Levin, 1989; Hall, Jaffe, and Trajtenberg, 2005; Lanjouw and Schankerman, 2004; Eizenberg, 2014) — whose applicability varies by industry. For instance, R&D expenditures and patents as measures of innovative activity may be appropriate in certain contexts (e.g., for semiconductor manufacturers), but not for others (e.g.,

[2] Linking the organizational and technological examples, Bartel, Ichniowski, and Shaw (2007) and Bresnahan, Brynjolfsson, and Hitt (2002) demonstrate that the adoption of new technologies can itself correspond to changes in the organizational practices of a firm, and consequently the skills required of workers.

among restaurants or law firms). Alternate existing proxies for firm performance (e.g., total factor productivity, spending on design and spending on business development (Corrado and Hulten, 2010)) are broadly comparable across industries. However, the data necessary to compute such measures exist only for a subset of firms: either publicly-traded firms or manufacturing firms, and may conflate non-innovative investments. Since our measure relies on the types of workers that employers seek — something that can be measured for nearly all firms – our methodology is applicable for all industries and for both privately held and publicly traded firms. So long as firms advertise for workers, our job title measure can be employed as a measure of innovation.[3] Second, our job-title based measure complements existing measures by capturing various stages of the innovation process. Compared to R&D spending and patenting — which measure firms' efforts to develop new product and process innovations — our job title measure also captures the application of successful inventions. A third and critical advantage of our measure is its ability to distinguish between innovation at the product and process levels, versus at the organizational level. Since the measure relies on job titles, it can then be mapped to occupational categories enabling it to distinguish between innovation at the technical worker level and that at the business level (i.e., sales, legal, managerial, etc.).

After introducing this dataset, we perform three exercises. The goal of these exercises is to corroborate our hypothesis that newer vintage job titles reflect new technologies and organizational practices (while receding job titles embody soon-to-be obsolete technologies and practices.) We first document that job postings with emerging job titles have higher than average educational requirements. Second, we show that newer vintage occupations tend to have higher posted salaries. And, third, newer vintage jobs more frequently require that prospective employees be familiar with new information and communication technologies (ICTs).

We then turn to our paper's main focus: the relationship between firm characteristics and the types of jobs they seek to fill. We find that while the relationship between contemporaneous productivity and job vintage is ambiguous, firms posting vacancies pertaining to new work have higher future growth and are more R&D intensive. We interpret these patterns as indicating that the adoption of new job titles are an innovative investment, costly at first

[3]For instance, Stanton and Thomas (2016) and Pelletier and Thomas (2018) employ data from an online job board — upWork (and its predecessor, oDesk) — in which firms advertise for jobs that will be performed remotely. These papers explore how intermediaries aid in matching firms to workers, how firms evaluate prospective employees, and which tasks are amenable to offshoring. Extending beyond remote work, Deming and Kahn (2018) apply data from Burning Glass — an aggregator of multiple online job boards — to study the relationship between firm productivity and their demand of "social skills" from their job applicants. Hershbein and Kahn (2018) and Modestino, Shoag, Ballance, et al. (2019) use these same data to explore the impact of the Great Recession on firms' labor demand.

yet increasing future profitability. Next, we find that younger firms post newer vintage jobs, and that the private firms that post newer vintage jobs are then more likely to go public in the future. This suggests that the private, and presumably younger (i.e., startup), firms investing in workers with novel skill combinations are also then more successful.

We then classify jobs into their primary function — technological versus organizational. Technological jobs are in computer, and engineering-related occupations; organizational jobs are in managerial, law, sales, and human resource-related occupations. We find that technological jobs tend to be of newer vintage than organizational roles, suggesting that innovation more frequently occurs on the product rather than the organizational margin. Consequently, hiring for technology jobs then correlates with better firm performance. Such firms are, more likely to be publicly traded, more productive, spend more on R&D (relative to sales) and survive longer. When taking a deeper look, however, we find that while there is less innovation within organizational roles, firms that do innovate by hiring for newer vintage organizational jobs are younger, more likely to become public and go on to survive longer. In fact, public firms hiring for highly innovative technology workers are less likely to survive. These findings suggest that there is a time in the firm life cycle to innovate on the product margin – namely at the early stages when creating a viable product is the top priority.[4] However, getting past this to then survive in the long run involves creating a sustainable and scalable business. These latter aspects involve investing in organizational workers with the novel skill sets necessary to adapt to a changing technological product landscape.

Our empirical exercises show that there is heterogeneity in the vintage of workers firms hire, both within and across industries. Firms that innovate in hiring are also innovative in how they organize and in the technologies they employ. Being on the hiring cutting edge is important for firms that succeed, as is locating closer to the technological frontier. However, firms are resource constrained and once they move past establishing their product market, growing this market involves allocating resources towards innovating on the more human, organizational aspects of the business, even though this happens less frequently and is perhaps more difficult to do. Firms that survive in the long run appear to locate on the technological frontier, but after a point, the returns to investing in pushing that frontier out appear to be far outweighed by the returns to organizing the business side of the firm in innovative ways. This trade-off offers another sliver of evidence for how Schumpeterian creative destruction (Schumpeter, 1942) can occur. Investing in cutting edge technological work comes at the cost of survival for established firms. Given this, it makes sense that

[4] In contrast to product innovation the the early stages, investing in breakthrough technologies at later stages presents the risk of cannibalizing one's own existing core business.

startups can enter and dominate technology spaces that might otherwise seem well primed for the more powerful incumbents. The list of Fortune 500 companies in the US clearly illustrates this churn: Only 12 percent of the companies listed in 1955 remain in 2017.

The remainder of our paper is structured as follows. Section 2 relates our work to the recent literature within economics and management on innovative activity, firm personnel practices, and firm performance. Section 3 then discusses the source data, our measurement of job vintages, and explores the correlates of emerging and disappearing work, at the ad level. Section 4 characterizes the types of firms which post emerging and disappearing work. Section 5 concludes.[5]

2 Related Literature

These results build on and contribute to multiple literatures in management and economics. Among these, the most closely related literature focuses on the (firm- and industry-level) costs and benefits of technology adoption. The benefit that firms' accrue from technology adoption depend their capacity to internalize and then successfully commercialize new technologies. Cohen and Levinthal (1990) hypothesizes that organizations' absorptive capacity depends on both on its individual members' and the whole organization's ability to exploit the new knowledge embedded within the innovation. While absorptive capacity can be developed either internally or externally (including by hiring new personnel), the latter must be complemented by existing talent. In other words, not all firms have the ability to adopt new technology successfully by simply hiring for the appropriate skills. There have to be existing systems in place to absorb this new knowledge in order to successfully commercialize the technology. Without this capacity, firms may not have the interest or ambition in technology adoption.

Even if a firm has the absorptive capacity for technology adoption, it may not always make financial sense for it to do so. Helfat and Winter (2011) emphasize the costs of technology adoption in assessing firm strategies. Firms trade off investing in existing capabilities that enhance current profits, versus ones that are geared towards innovation and future profits. Investing in newer vintage workers reflects a firms' choice to prioritize innovation to secure future growth; hiring old vintage workers signals a firms' choice to focus on current operational capabilities. In fact, evidence from (Henderson, 1995; Adner and Snow, 2010) shows that under certain conditions, firms can perform well over long periods in the absence

[5] In the appendices, we outline our measurement of posted salaries, the identity of the posting firm, and job titles (Appendix A), list job titles that are emerging and disappearing within each decade of our sample (Appendix B.1), and compare my measures of emerging job titles Lin (2011)'s measures of new work (Appendix B.2).

of technological innovation. This typically occurs when the value chain itself is best suited to the existing technology and where customers are already well served. In such circumstances, it is then rational for managers to strategically avoid core technology investments and instead invest in process improvements or organizational innovations, if even. As a specific example, Henderson (1995) finds in her study of the optical lithography industry that old technologies prevailed far beyond their predicted life span.[6, 7] These arguments relate to an older literature on product versus process innovation (Abernathy and Utterback, 1978; Henderson and Clark, 1990; Klepper, 1996). Not only do firms trade off profits today versus in the future by choosing to innovate, they must also account for whether they are better served doing so on the product or on the business margin. Once the firm has established a stable market for its product, it then faces the very real risk of replication from competitors. Therefore, the firm is faced with making the decision of whether to allocate resources towards pushing out the product technology frontier, or whether to invest in the process of production and distribution so as to reduce per unit costs and increase market share. Consistent with Helfat and Winter (2011), our results suggest that hiring new vintage workers relates to future gains, likely at the cost of current returns. However, consistent with the arguments in Abernathy and Utterback (1978); Henderson and Clark (1990); Klepper (1996), whether the gains come from the product or process margins depends on where the firm is situated in terms of its life-cycle.

Our findings also complement an extensive literature on firm heterogeneity. As is already well-understood, even within narrowly defined product markets, firm behavior, capabilities, and performance vary enormously. Moreover, exceptionally productive and profitable firms tend to be exceptional along a number of dimensions: They are more likely to adopt best management practices (Bloom and Van Reenen, 2007; Bloom, Eifert, Mahajan, McKenzie, and Roberts, 2013), employ highly educated workers (Fox and Smeets, 2011), use high quality intermediate inputs (Kugler and Verhoogen, 2009), enter into multiple export markets (Eaton, Kortum, and Kramarz, 2011), and patent (Balasubramanian and Sivadasan, 2011). To date, however, it has been difficult to measure, in a manner consistent across firms,

[6] Baldwin and Lin (2002) enumerate the many impediments that firms may face when adopting new technologies, ones that are related to implementation costs; regulatory and tax policy; the availability of workers capable of using the new technologies; internal organizational problems; and a lack of information about the new technology. In addition, given the uncertainties around the returns to adoption and the associated fixed costs, only firms with the ability to evaluate these technologies will be early adopters (Wozniak, 1987).

[7] Adner and Levinthal (2001) points out that most of the prevailing explanations of technology adoption ignore the demand side, namely whether consumers of the firms' end product value these costly innovations. This paper provides an intuitive illustration of this within the pen industry. While the pen industry shifted from the fountain to ball point technology, companies like Pelican and Waterman successfully found niche positions as leading makers of fountain pens, rather than adopt the new technology.

the vintages of the production techniques used by firms. Our contribution to the literature on firm heterogeneity is to develop such a measure and validate that it predicts future performance.

Finally, it should be noted that we are not the first to propose the use of job titles in the study of innovation. In his work on the agglomeration of innovation, Lin (2011) creatively proposes the use of job titles to identify new work within the census occupation classification system. This allows him to classify new job titles, as they appear over long horizons. The key novelty in our measure, which looks at job postings rather than formal occupational classifications, is that we are to identify the firms that are searching for individual job titles.[8]

It is clear that researchers have taken a variety of angles to address how and why technology adoption might affect firm performance. Our results confirm many of these theoretical predictions and empirical findings within individual industries. A key advantage to our job titles measure combined with the broad set of industries available to us, is that we can evaluate the implications of various hypotheses proposed across literatures within this one paper.

3 Data and Measurement Issues

3.1 Data Source and Variables

Our new dataset is drawn from ads which were originally published in the *Boston Globe, New York Times, and Wall Street Journal.* Atalay, Phongthiengtham, Sotelo, and Tannenbaum (2018, 2019) outline the algorithm for transforming the unprocessed newspaper text into a structured database. There, we describe how to extract, from each vacancy posting, information on the ad's job title, the tasks which the worker is expected to perform, and the technologies that the worker uses on the job. We also delineate how we assign a Standard Occupation Classification (SOC) code to each job title.[9] The dataset contains 9.26 million

[8] We introduced our measure of job title vintages in an earlier paper (Atalay, Phongthiengtham, Sotelo, and Tannenbaum, 2019). In this earlier paper, we linked job title vintages to the types of tasks workers were expected to perform, and did not extract information on the firm posting the ad.

[9] The main task categories correspond to measures explored by Spitz-Oener (2006): nonroutine analytic, nonroutine interactive, and nonroutine manual tasks; and routine cognitive and routine manual tasks. Atalay, Phongthiengtham, Sotelo, and Tannenbaum (2019) describes the full set of job ad words which correspond to each of these five task groups. The 48 technologies include office ICTs (e.g., Microsoft Excel, Microsoft PowerPoint, Microsoft Word, WordPerfect), hardware (e.g., IBM 360, IBM 370), general purpose software (e.g., C++, FORTRAN, Java); see Atalay, Phongthiengtham, Sotelo, and Tannenbaum (2018) for a full list of the technologies. The Standard Occupation Classification is an occupational classification system developed by the United States government. By assigning an SOC code to each job title, one may link our database of job ads' task and technology mentions to surveys developed and maintained by governmental

ads from 1940 to 2000. In this paper, our focus is on the dates at which each job title — already extracted in our previous work — appear in our newspaper text. Since our measures of job title emergence and disappearance are computed based on the distribution of dates in which the job title appeared, we restrict attention to job titles which appear sufficiently frequently, in at least 40 distinct ads through the sample period. With this restriction, the benchmark dataset contains 4.99 million job ads.

New to this paper, whenever possible we attempt to retrieve the firm or employment agency which placed the ad, as well as the job's posted salary. To recover information on the posting party, we search for certain string types that tend to appear in conjunction with the name of a firm: "agency," "agcy," "associate," "associates," "assoc," "co," "company," "corp," "corporation," "inc," "incorporated", "llc," "personnel." We also search for instances of a 7-digit number (which would indicate a phone number), or a set of strings which would indicate an address of the posting firm. When these string types occur, we examine the surrounding words, and then manually group common firms. (As much as possible, we consistently record firms' identities, even in cases in which naming conventions differ within the sample period.) Among the 4.99 million ads which will form the basis for the analysis, below, we could extract information on the posting party for 678 thousand ads. For these 678 thousand ads, we could identify only a phone number or address for 130 thousand ads. For 239 thousand ads, the posting party we identified was an employment agency. For the remaining 309 thousand ads, we have identified an employer who is placing the ad on its own behalf. Among these, for 118 thousand ads we could then match the identity of the posting party to the Compustat dataset. Finally, to retrieve information on the posted salary, we again search for groups of strings that tend to reflect a person's salary. Among the 4.99 million ads that form the base sample, we could extract information on the posted salary for 185 thousand ads. Appendix A provides additional information on algorithms with which we group job titles, identify posted salaries, and identify the firm or employment agency which is posting the job ad. In the same appendix, we also illustrate the performance of these algorithms through an example page of ads.

3.2 Measuring Job Vintages

For each job title j, we compute a pair of statistics measuring the dates at which the job title was introduced and disappeared from our dataset. Quoting from our earlier work, we "define v_j^p, *vintages* of job title j, as the p^{th} quantile of the distribution of years in which the job title appears in our data. In computing these quantiles, for each job title, we weight

agencies (e.g., the American Community Survey, the Current Population Survey).

according to the job title's share of ads (S_{jt}) in each year. For p close to 0, v_j^p compares different job titles based on when they first emerged in our data set. In contrast, v_j^p for p close to 1 compares job titles based on their disappearance from our dataset." Atalay, Phongthiengtham, Sotelo, and Tannenbaum (2019) Our main analysis centers around $v_j^{0.01}$ as our measure for the year in which job title j entered the dataset and $v_j^{0.99}$ as our measure for year in which job title j left the dataset.[10]

Figure 1 illustrates the construction of these percentiles of two job titles. There, we plot the share of ads for which the job title equals *Figure Clerk* or *Comptometer Operator*. These are two job titles for different types of financial clerical work. At its peak, in the late 1940s and early 1950s, approximately 0.2 to 0.3 percent of all ads within the newspaper data were for *Comptometer Operators.* By 1970, few if any job ads were for a *Comptometer Operator* position. On the other hand, *Figure Clerk* was rarely mentioned in the 1940s. Then, beginning in the 1950s there was a slow, steady increase in the number of job ads for which *Figure Clerk* was the job title. To depict the time-span over which each of these two job titles were in use, we plot two vertical lines. For the *Comptometer Operator* job title, the 1st and 99th percentile periods in which the title was mentioned are 1942 and 1967. In other words, $v_j^{0.01} = 1942$ and $v_j^{0.99} = 1967$ for $j =$Comptometer Operator. Analogously, for $j =$Figure Clerk $v_j^{0.01} = 1956$ and $v_j^{0.99} = 1982$.

In Appendix B, we expand on these results. First, in Appendix B.1, we present the most frequently occurring job titles based on the decade in which they appeared or disappeared from usage in our job ad text. Then, in Appendix B.2 we compare $v_j^{0.01}$ — our measure of the date in which job title j appears in the newspaper vacancy posting data — to Lin (2011)'s measure of new work. In that paper, Lin compares revisions of the Dictionary of Occupational Titles (revisions which occurred between 1965 and 1977, and between 1977 and 1991) and the Census Classified Indexes (a revision which occurred between 1990 and 2000) to identify new job titles. In this appendix, we establish that our $v_j^{0.01}$ aligns with Lin (2011)'s measure of new work: $v_j^{0.01}$ is lowest for job titles already present in the 1965 Dictionary of Occupational Titles, then higher for job titles which appeared in the 1977 revision of the Dictionary of Occupational Titles, higher still for job titles which appeared in the 1991 revision, and highest for job titles which only appeared in the 2000 edition of the Census Classified Indexes.

[10] Our measures of the years of job title entry and exit correspond to the $p = 1^{\text{st}}$ adn $p = 99^{\text{th}}$ percentiles of the years in which they appeared in our dataset. The choice of the cutoff reflects a balance between the following two considerations. On the one hand, choosing a p closer to the endpoints leads to a measure more sensitive to a few outlier observaitons. On the other hand, choosing a p closer to 0.50 yields a measure less directly related to entry or exit.

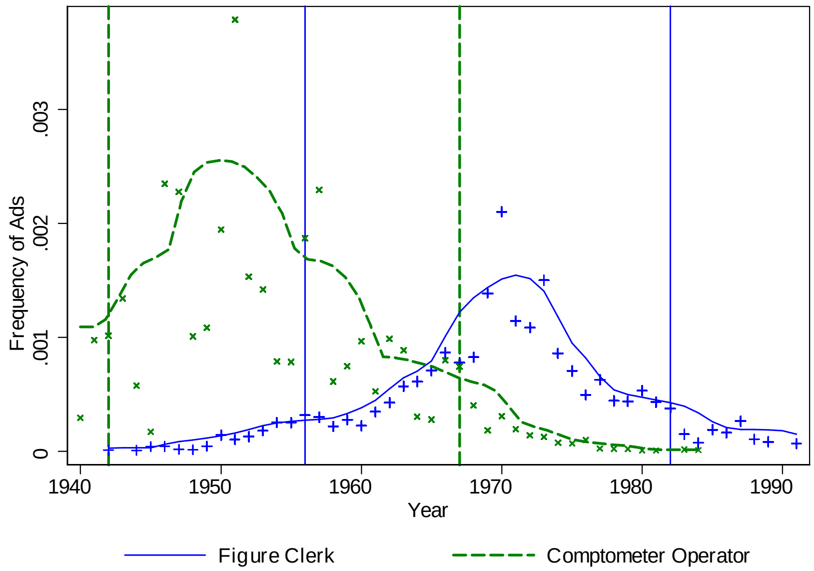

Figure 1: Job title frequencies.
Notes: We plot the frequency of two individual job titles for each year between 1940 and 2000. The vertical lines depict $v_j^{0.01}$ and $v_j^{0.99}$ for each of the two titles. The smoothed lines are computed using a local polynomial smoother. Within the 1940 to 2000 sample, there were 4544 ads for Figure Clerks and 5772 ads for Comptometer Operators.

3.3 Characteristics of Emerging and Disappearing Work

Before exploring the relationship between ads' job title vintages and characteristics of the firms that post these ads, we establish three characteristics of emerging and disappearing work. First, for vacancy postings in which the employer posts a salary, newer jobs have on average higher posted salaries. Second, newer vintage jobs tend to also include mentions of new technologies. And, third, job ads corresponding to newer vintage jobs also include degree (either bachelors or graduate) requirements. To emphasize, these three relationships should be afforded a descriptive, not causal, interpretation. The goal of these exercises is to illustrate that new and disappearing job titles are, respectively, meaningfully different from existing and surviving job titles. New job titles reflect a reorganization of production toward innovative, skill-complementing techniques.

In the first columns of Table 1, we compare jobs' posted salaries to the job title vintage using a regression characterized by the following equation:

$$\log\left(\text{salary}_a\right) = \beta_{\text{hourly}} + \beta_{\text{weekly}} + \beta_{\text{annual}} + \beta_t + \beta_o + \beta_1 \cdot v_{j(a)}^{0.01} + \beta_2 \cdot v_{j(a)}^{0.99} + \epsilon_a \qquad (1)$$

In this equation, $\log\left(\text{salary}_a\right)$ equals the stated salary in job ad a. Since the posted salary may be listed as an annual, weekly, or yearly wage, we include fixed effects to place these posted salaries on a comparable scale. In addition, we include controls for the year in which the ad was posted, the (4-digit) SOC occupation, and the job's task content. The coefficients of interest are β_1 and β_2, measuring the association between salary and the job title vintage of the posted ad a. The first columns of Table 1 indicate that new jobs pay higher salaries, both unconditionally and conditional on occupation code. According to the estimates of column (2), a 5-year increase in job vintages is associate with a 1.3 log point increase ($\approx 5 \cdot (0.0017 + 0.0010)$) in salaries. According to columns (3) and (4), the relationship between salary and new work is localized primarily in the second half of our sample. As highly skilled workers tend to be better remunerated, the estimates in columns (1) through (6) align with Greenwood and Yorukoglu (1997) and Caselli (1999). There, the authors argue that skilled individuals have a comparative advantage in using new technologies.

Building on this idea, we compare the frequency of new technologies or high skills and job title vintages. In the remaining columns of Table 1, we compare technology mentions or degree requirements and job title vintages using a regression characterized by the following equation:

$$y_a = \beta_t + \beta_o + \beta_1 \cdot v_{j(a)}^{0.01} + \beta_2 \cdot v_{j(a)}^{0.99} + \epsilon_a \tag{2}$$

In columns (5) and (6), y_a equals the frequency of new technology related words (mentions per 1000 job ad words) in job ad a and $j(a)$ refers to the job title associated with ad a. In the remaining columns, y_a equals the frequency of mentions of an undergraduate degree requirement (columns 7 through 10) or a graduate degree requirement (columns 11 and 12). Using the specifications which condition on occupation fixed effects, we find that a one decade increase in job title vintages is associated with a 0.11 standard deviation increase job ads' technology mentions, a 0.02 standard deviation increase in undergraduate degree mentions, and no difference in graduate degree mentions.[11]

In sum, the job vintage measures are correlated with innovative, new, high-skilled activity.

[11] Within the sample of ads posted between 1970 and 2000, there were 1.56 mentions of one of our ICTs per 1000 job ad words; the standard deviation across ads equals 8.92 mentions (per 1000 job ad words). So, a one decade increase in $v_j^{0.01}$ and $v_j^{0.99}$ translates to a $0.96 (\approx 10 \cdot (0.044 + 0.052))$ increase in technology mentions per 1000 ad words, equivalent to $0.11 (\approx 0.96/8.92)$ standard deviations of our ICT measure.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	Log Salary				Technology	
Year of Emergence	0.0017	0.0017	0.0000	0.0022	0.117	0.044
	(0.0002)	(0.0002)	(0.0004)	(0.0002)	(0.001)	(0.001)
Year of Disappearance	0.0035	0.0010	0.0003	0.0043	0.074	0.052
	(0.0002)	(0.0002)	(0.0003)	(0.0005)	(0.001)	(0.001)
Mean of Dep. Variable					1.56	
Std. Dev. of Dep. Variable	0.64		0.52	1.12	8.92	
SOC F.E.	No	Yes	Yes	Yes	Yes	Yes
Sample	1940-2000		1940-1969	1970-2000		
	(7)	(8)	(9)	(10)	(11)	(12)
Dep. Variable	Undergraduate Degree				Graduate Degree	
Year of Emergence	0.0117	0.0061	0.0106	0.0055	-0.0037	-0.0079
	(0.0003)	(0.0003)	(0.0008)	(0.0003)	(0.0005)	(0.0006)
Year of Disappearance	0.0078	0.0029	0.0038	0.0055	0.0359	0.0099
	(0.0002)	(0.0003)	(0.0003)	(0.0008)	(0.0005)	(0.0006)
Mean of Dep. Variable	0.56		0.44	0.72	1.67	
Std. Dev. of Dep. Variable	4.12		3.70	4.62	7.64	
SOC F.E.	No	Yes	Yes	Yes	No	Yes
Sample	1940-2000		1940-1969	1970-2000	1940-2000	

Table 1: Relationship between job title vintage and salaries; technology measures.

Notes: The coefficient estimates and standard errors in columns (1) through (4) correspond to estimations of Equation 1. The coefficient estimates and standard errors in columns (5) through (12) correspond to estimations of Equation 2. In columns (1) through (4) the sample standard deviation refers to the root mean squared error of the log (salaray), after conditioning on the frequency (annually, weekly, or hourly) at which salaries are stated. The sample in columns (1) and (2) contains 172 thousand observations for which we could identify the salary, which the occupation code is non-missing, and for which job title j is mentioned at least 40 times in our sample period. The sample in columns (7), (8), (11), and (12) contains 4.8 million observations for which job title j is mentioned at least 40 times in our sample period and for which the occupation code is non-missing. SOC F.E. refers to fixed effects for the 4-digit SOC of each ad.

4 Job Vintages and Firm Characteristics

Having demonstrated that job vintages are correlated with other work characteristics indicative of innovative activity, we characterize the firms which place ads for emerging and disappearing work. In Section 4.1, we provide a first statistical analysis of the average job vintages among the ads placed by each firm and the firm's current and future performance. Then, in Section 4.2, we assess whether the relationships among job vintages and firm characteristics depends on the broad type of jobs — technological versus organizational — that the firm is advertising. To close this section, in Section 4.3 we illustrate through narrative examples on the relationship between firm performance and job vintages. We compare DEC and Wang Laboratories — two firms which, in the 1960s and 1970s respectively advertised for newly emerging work — to American Biltrite, Barton's Candy, and Kennecott Copper — three firms which sought out employees to perform jobs which were soon to disappear.

4.1 Benchmark Statistical Analysis

Our initial set of regressions compares firm-level productivity, R&D intensity, and future sales growth to measures of job vintage. For the ads that a firm f places in year t, we average over the job vintage measures that we introduced in the previous section:

$$\text{Avg. Year of Emergence}_{ft} = \frac{1}{|A_{ft}|} \sum_{a \in A_{ft}} v_{j(a)}^{0.01} \tag{3}$$

$$\text{Avg. Median Year}_{ft} = \frac{1}{|A_{ft}|} \sum_{a \in A_{ft}} v_{j(a)}^{0.50} \tag{4}$$

$$\text{Avg. Year of Disappearance}_{ft} = \frac{1}{|A_{ft}|} \sum_{a \in A_{ft}} v_{j(a)}^{0.99} \tag{5}$$

In these equations, A_{ft} refers to the set of ads that firm posted in year t and $|A_{ft}|$ to the number of ads within this set.

Our comparisons are based on the following regression specification:

$$\begin{aligned} x_{ft} = \beta_t + \beta_1 \cdot \text{Avg. Year of Emergence}_{ft} + \beta_2 \cdot \text{Avg. Median Year}_{ft} \\ + \beta_3 \cdot \text{Avg. Year of Disappearance}_{ft} + \gamma X_{ft} + \epsilon_{ft} \end{aligned} \tag{6}$$

Within Equation 6, x_{ft} represents either firm-year level labor productivity, R&D intensity, or future sales growth; β_t are year-level fixed effects; and, X_{ft} are firm-level controls. These include the firm's book value of total assets, employment, revenues; the fraction of the firm's ads that are in each 2-digit occupation code in year t; and 2-digit industry-level fixed effects. The coefficients of interest, β_1, β_2, and β_3 thus characterize the relationship between firms' propensity to post ads for emerging and disappearing job titles on the one hand, and productivity, R&D intensity, and future sales growth on the other hand. To emphasize, by including year-level fixed effects (β_t), our comparisons between job vintages and other firm characteristics exploit variation across firms within a given year.

Table 2 presents the results from this exercise. Here, the sample includes the set of firm-year observations for which the name of the posting firm could be matched to a firm in the Compustat database and where the firm was publicly traded in the year during which the ad was posted. The first four columns of Table 2 suggest that there is little relationship between firms' job vintage and their contemporaneous labor productivity. None of the coefficient estimates within the first three columns are statistically significant. Including firm fixed effects (as we do in column 4), firms' labor productivity is higher when posting fewer disappearing vintage (low $v_{j(a)}^{0.99}$) jobs. Columns (5) through (8) assess the relationships among job vintages and R&D intensity. Firms that post newly emerging job titles (high $v_{j(a)}^{0.01}$) and soon-to-be disappearing (low $v_{j(a)}^{0.99}$) job title are more R&D intensive. Firms' overall job vintages (as measured by the average of the $v_{j(a)}^{0.50}$ measure for the ads that the firms post) is positively correlated to their R&D-to-sales ratios, as well.

Columns (9) through (16) indicate that there is stark increasing relationship between firms' job vintage measures and future growth: Firms which post vacancies pertaining to new work have higher future growth. Firms which post ads for receding jobs have slower future sales growth and lower R&D. These differences are substantial: A decade increase in job vintage is associated with a 7 log point increase in sales growth over a five year horizon, and a 9 log point increase over a ten-year horizon. Columns (12) and (16) suggest that, even within firms, newer job vintages are predictive of future sales growth.

Table 3, compares firms' cohorts with the job title vintages that they post. To do so, we apply the regression specification given in Equation 6 with the firms' entry into, or exit from, the Compustat database as the dependent variable. (To emphasize, since we are controlling for the year in which the ad is posted, the relationships that are identified are not mechanically reflecting the passage of time within our sample.) According to the first three columns of Table 3, firms that have more recently entered the Compustat database tend to post newer-vintage jobs. For example, based on the estimates given in the third column, a 10 year increase in the vintage of firms' job ads is associated with a 1.3 year increase in the entry date. The association between exit date and job title vintage is even stronger. This suggests that younger (at least to the Compustat) firms are more likely to hire newer vintage workers and also then survive longer where the effect on survival is especially strong.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Variable	$\log\left(y_{ft}/l_{ft}\right)$				$\log\left(\text{R\&D}_{ft}/y_{ft}\right)$			
Avg. Year of Emergence$_{ft}$	-0.0021	-0.0019		0.0014	0.111	0.021		-0.018
	(0.0014)	(0.0015)		(0.0008)	(0.026)	(0.024)		(0.021)
Avg. Median Year$_{ft}$			-0.0023				0.049	
			(0.0014)				(0.024)	
Avg. Year of Disappearance$_{ft}$	-0.0008	0.0002		0.0037	0.142	0.091		0.012
	(0.0032)	(0.0029)		(0.0014)	(0.054)	(0.048)		(0.037)
Other Controls	Industry F.E.	Industry F.E., SOC Shares		Firm F.E.	Industry F.E.	Industry F.E., SOC Shares		Firm F.E.
Sample Mean	-0.331				-5.200			
Sample Std. Dev.	0.528				4.859			
Number of Obs.	5,252				5252			
Number of Ads	75,000				75,000			

	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Dep. Variable	$\log\left(y_{f,t+5}/y_{ft}\right)$				$\log\left(y_{f,t+10}/y_{ft}\right)$			
Avg. Year of Emergence$_{ft}$	0.006	0.004		0.003	0.006	0.006		0.004
	(0.002)	(0.002)		(0.001)	(0.002)	(0.002)		(0.001)
Avg. Median Year$_{ft}$			0.007				0.009	
			(0.001)				(0.002)	
Avg. Year of Disappearance$_{ft}$	0.008	0.006		0.002	0.008	0.007		0.001
	(0.002)	(0.002)		(0.001)	(0.003)	(0.003)		(0.001)
Other Controls	Industry F.E.	Industry F.E., SOC Shares		Firm F.E.	Industry F.E.	Industry F.E., SOC Shares		Firm F.E.
Sample Mean	0.391				0.607			
Sample Std. Dev.	0.290				0.336			
Number of Obs.	4,692				4,137			
Number of Ads	71,000				67,000			

Table 2: Relationship between job title vintage, productivity, R&D intensity, and sales growth.

Notes: The "SOC Controls" refer to variables which measure the share of ads, within the firm-year observation, corresponding to each 2-digit SOC code. The employment, sales, assets, and R & D data are computed using data from Compustat. The "Number of Ads" refers to the number of ads (rounded to the nearest thousand) in the regression sample.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	Entry Year to Compustat			Exit Year from Compustat		
Avg. Year of Emergence$_{ft}$	0.162	0.144		0.200	0.310	
	(0.025)	(0.028)		(0.059)	(0.067)	
Avg. Median Year$_{ft}$			0.131			0.342
			(0.022)			(0.065)
Avg. Year of Disappearance$_{ft}$	0.219	0.176		0.503	0.518	
	(0.039)	(0.035)		(0.100)	(0.100)	
Additional Controls	Industry F.E.	Industry F.E., SOC Shares		Industry F.E.	Industry F.E., SOC Shares	
Sample Mean	1956.2			2001.9		
Number of Observations	5,247			5,270		
Number of Ads (thousand)	75			75		

Table 3: Relationship between job title vintage firms' entry and exit from Compustat.
Notes: The "SOC Controls" refer to variables which measure the share of ads, within the firm-year observation, corresponding to each 2-digit SOC code. The "Entry Year into Compustat" variable refers to the first year in which the firm name appears in the Compustat database. Since the dataset's first observations are from 1950, this variable is censored from below at 1950 even for firms which were publicly traded before then. Among the 5247 firm-year observations, the entry year is equal to 1950 for 2192 observations. The "Exit Year from Compustat" variable refers to the last year in which the firm name appears in the same database. For firms that are still publicly traded, this variable is censored above in 2017. The exit year is equal to 2017 for 1549 observations.

Tables 4 and 5 expand our analysis beyond publicly traded firms. To begin, we compare job vintages for publicly-traded firms and privately held firms.[12] According to the first three columns of Table 4, publicly traded firms tend to post newer-vintage jobs. In the final three columns, we assess whether current job title vintages are predictive of *future* status. That is, for firms that have not yet been publicly traded, we estimate Equation 6. In this equation, x_{ft} is now an indicator variable equal to 1 if firm f becomes publicly traded on or before year $t+10$. Privately held firms which post newer jobs are substantially more likely to become publicly held in the future: A ten-year increase in job vintage is associated with a 3 percentage point increase (off of a base of 11.1 percent) in the probability of future public status. Consistent with the effect on firm growth as measured by sales, the finding here suggests that hiring for younger vintage workers once again relates positively to firm outcomes, given that the most successful private firms (or startups) are typically the ones to go public.

Our finding that job vintages predict future entry into publicly traded status could potentially reflect either firm survival or entry to publicly traded status conditional on sur-

[12] We characterize a firm as privately held if we cannot match it to a firm in the Compustat database in the year of the ad's posting. To be certain, this definition will inevitably lead us to overstate the share of ads posted by privately held firms.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	Publicly Traded			Soon to be Publicly Traded		
Entering	0.014	0.007		0.003	0.005	
Vintage$_{ft}$	(0.002)	(0.002)		(0.001)	(0.001)	
Median			0.007			0.003
Vintage$_{ft}$			(0.001)			(0.001)
Disappearing	0.005	0.000		-0.000	-0.000	
Vintage$_{ft}$	(0.002)	(0.003)		(0.002)	(0.002)	
Additional Controls	None	SOC Shares		None	SOC Shares	
Sample Mean		0.316			0.111	
Number of Observations		20,367			14,339	
Number of Ads (thousand)		239			158	

Table 4: Relationship between job vintage and publicly traded status.

Notes: The "SOC Controls" refer to variables which measure the share of ads, within the firm-year observation, corresponding to each 2-digit SOC code. Within the second three columns, the dependent variable "Soon to be Publicly Traded" is an indicator variable, equal to 1 if the posting firm can be matched to a publicly taded firm in the Compustat database, entering the database within 10 years of the ad's posting. Within these columns, the sample includes observations for which the firm has not entered the Compustat database at the time of the ad's posting and in which the ad was posted before 1990.

vival. We measure firm survival based on the firms' future advertising behavior: If in our newspaper text, we observe the firm posting a job ad in year $t+10$ or later, we define the firm to have survived to year t. For the subset of privately held firms which survive to at least 10 years, we again characterize the relationship between firms' propensity to soon become publicly traded and the job vintages of the ads they are currently posting. Again, firms which post ads for emerging work are more likely to become publicly traded in the near future.

To sum up, while firms with newer vintage jobs are not necessarily more productive contemporaneously, they are more innovative and have faster growth in the future. To arrive at this conclusion, we compare publicly traded firms' job vintage to their R&D intensity, to future sales growth, and to the year in which the firm entered and exited from the universe of publicly traded firms. We then show that — among privately-held firms — firms that post newer vintage jobs are more likely to be publicly traded in the future

4.2 Organizational and Technological Vintages

In this section, we assess whether the relationships between job vintages and firm characteristics that we identified in the previous section are due to certain types of jobs.

We first classify job titles based on their primary function: organizational versus technological. In Table 6, we compare firms' propensity to post ads for jobs in organizational

Dep. Variable	(1)	(2)	(3)	(4)	(5)	(6)
	Publicly Traded Within 10 Years?			Post Ads in Newspaper $\geq$ 10 Years Later?		
Avg. Year of Emergence$_{ft}$	0.005	0.007		-0.0034	-0.0036	
	(0.002)	(0.002)		(0.0018)	(0.0020)	
Avg. Median Year$_{ft}$			0.004			-0.0001
			(0.002)			(0.0013)
Avg. Year of Disappearance$_{ft}$	-0.004	0.001		0.0039	0.0011	
	(0.003)	(0.002)		(0.0016)	(0.0018)	
Additional Controls	None	SOC Shares		None	SOC Shares	
Sample Mean		0.142			0.749	
Number of Observations		8,659			14,283	
Number of Ads (thousand)		116			160	

Table 5: Relationship between job vintage, publicly traded status, and firm survival.
Notes: The "SOC Controls" refer to variables which measure the share of ads, within the firm-year observation, corresponding to each 2-digit SOC code. Within the first three columns, the dependent variable "Soon to be Publicly Traded" is an indicator variable, equal to 1 if the posting firm can be matched to a publicly traded firm in the Compustat database, entering the database within 10 years of the ad's posting. Within these columns, the sample includes observations for which (i) the firm has not entered the Compustat database at the time of the ad's posting, (ii) in which the ad was posted before 1990, and (iii) the firm has at least one at posted 10 years after the ad's posting. In the second three columns, the dependent variable is equal to 1 if the firm survives at least 10 years (has at least one job ad ten years after the ad's posting.) The sample includes all ads posted before 1990, posted by firms that have not entered the Compustat database.

or technological occupations to other firm characteristics. Organizational job ads refer to occupations with 2-digit SOC codes equal to 11 (Managerial), 13 (Financial), 23 (Legal), 41 (Sales) and 43 (Administrative and Clerical); technological job ads refer to occupations with 2-digit SOC codes equal to 15 (Computer) or 17 (Engineering).[13] Among the sample of all firms, we find publicly-traded firms tend to post a greater frequency of ads in technological occupations, fewer ads in organizational occupations. Second, technological occupations tend to contain, on average, newer vintage jobs; organizational occupations correspond to older vintage jobs. Third, restricting attention to publicly traded firms, firms posting a greater frequency of organizational occupation job ads tend to be higher labor productivity, have lower R&D expenditures (relative to their sales), and are more likely to exit from the sample of publicly traded firms.

We now test for whether product innovations and business (or process) innovations

[13] There is a residual group of occupations which are neither technological nor organizational. These include 2-digit SOC codes equal to 19 (Life, Physical, and Social Science), 21 (Community and Social Service), 25 (Education, Training, and Library), 27 (Arts, Design, Entertainment, Sports, and Media), 29 (Healthcare Practitioners and Technical), 31 (Healthcare Support), 33 (Protective Service), 35 (Food Preparation and Serving), 37 (Building and Grounds Cleaning and Maintenance), 39 (Personal Care), 45 (Farming, Fishing, and Forestry), 47 (Construction and Extraction), 49 (Installation, Maintenance, and Repair), 51 (Production), 53 (Transportation and Material Moving), and 55 (Military).

	Organizational	Technological
Publicly Traded	-0.06	0.16
Median Vintage	-0.22	0.16
$\log(y_{ft})$	-0.05	0.05
$\log(l_{ft})$	-0.08	0.07
$\log(y_{ft}/l_{ft})$	0.10	-0.07
$\log(y_{f,t+5}/y_{ft})$	-0.06	0.02
$\log(\text{R\&D}_{ft}/y_{ft})$	-0.22	0.25
Entry Year to Compustat	0.02	0.03
Exit Year from Compustat	-0.13	0.10

Table 6: Correlations Between Firm Characteristics and the Fraction of Organizational and Technological Advertisements

Notes: For each variable, we regress the variable against year-level fixed effects, then take the residual. This table presents the correlation between this residualized versions of firm-level characteristics the fraction of firms' job ads which correspond to organizational or technological occupations. Observations are weighted by the number of ads in the firm-year cell. The first five rows of correlations draw on a sample of 20,362 firm-year observations corresponding to 239 thousand job ads. The last two rows restrict the sample to 5252 firm-year observations of publicly traded firms, corresponding to 75 thousand job ads. With the exception of the correlations corresponding to the "Entry Year to Compustat" row, all correlations are statistically significant at the 1 percent level.

are substitutes or complements. We seek to understand whether resource constrained firms choose to innovate on just one or both margins (product or process) and whether they focus more intensely on one aspect versus the other depending on their position in the firm life-cycle (Abernathy and Utterback, 1978). Given that few firms have the resource abundance to focus on all margins of innovation simultaneously, this exercise sheds light on the trade-offs firms face when focusing on product versus business side innovations.

Like Equation 4, we construct a measure of the average vintages of the ads that firms post within each period. We now do so separately across different groups of occupations:

$$\text{Average Median Year: Organizational}_{ft} = \frac{\sum_{a \in A_{ft} \cap j(a) \in \{\text{organizational}\}} v_{j(a)}^{0.50}}{|A_{ft} \cap j(a) \in \{\text{organizational}\}|} \tag{7}$$

$$\text{Average Median Year: Technological}_{ft} = \frac{\sum_{a \in A_{ft} \cap j(a) \in \{\text{technological}\}} v_{j(a)}^{0.50}}{|A_{ft} \cap j(a) \in \{\text{technological}\}|} \tag{8}$$

In these equations, $A_{ft} \cap j(a) \in \{\text{organizational}\}$ refers to the set of ads that firm f posts in period t for which job title j falls within an organizational occupation. The "Median Vintage Organizational$_{ft}$" measure then computes the average vintage among this set of ads. We compute analogous measures for the average vintages of technological jobs, the average vintage of non-organizational jobs, or the average vintage of non-technological jobs, and so on. Table 7 assesses within-firm correlations in the occupations' vintages. We find,

Dep. Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Avg. Median Year: Organizational$_{ft}$				Avg. Median Year: Technological$_{ft}$			
Avg. Median Year: Non-Organizational$_{ft}$	0.048 (0.021)	0.062 (0.012)	0.061 (0.011)	0.016 (0.010)				
Avg. Median Year: Non-Technological$_{ft}$					0.076 (0.036)	0.061 (0.026)	0.068 (0.022)	0.025 (0.022)
Sample	Public	Private	Public + Private		Public	Private	Public + Private	
Additional Controls		None		Firm F.E.		None		Firm F.E.
Number of Observations	3244	7922	11166		2522	4985	7507	
Numb. of Ads (thousand)	71	144	214		60	103	163	

Table 7: Relationships among job vintages of different occupation types

Notes: Within each regression, our specification includes year fixed effects and the fraction of job ads within each 2-digit SOC occupation.

in columns (1) through (3) that firms posting newer vintage organizational tasks also tend to post newer vintage job titles in other occupational categories. These relationships pertain both to firms that are publicly traded and privately listed. In columns (5) through (7), we find a similar relationship when focusing on technological occupations: firms posting newer vintage job titles within technological occupations also tend to post newer vintage job ads in other fields. In columns (4) and (8), our regression specifications include firm fixed effects. While not statistically significant, the estimated coefficients from these columns suggest that when firms update their workplace practices in one domain also tend to update their practices in other domains. These relationships are consistent with past work on complementarities in organizational design (Bresnahan, Brynjolfsson, and Hitt, 2002).

Having established that (i) firms' propensity to advertise for technological (as opposed to organizational) jobs are larger, more R&D intensive and post newer vintage jobs and that (ii) vintages are correlated within firms, turn in the remainder of this section to heterogeneity, across occupation types, in the relationships among firm characteristics and job vintages. Are the relationships that we documented in the previous subsection due primarily to organizational jobs or to technological jobs

In Table 8, we begin by re-assessing the positive relationships among job vintages,R&D intensity, future sales growth that we explored in Table 2. According to the first three columns of Table 8, we find the relationship between R&D intensity and job vintages is primarily driven by technological occupations. On the other hand, the relationship between job vintage and sales growth is due to non-technological occupations.

Table 9 builds on our Table 3-4 analysis relating job vintages, publicly-traded sta-

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	$\log\left(\text{R\&D}_{ft}/y_{ft}\right)$			$\log\left(y_{f,t+5}/y_{ft}\right)$		
Avg. Median Year:	0.039		0.034	0.0029		0.0022
Organizational$_{ft}$	(0.027)		(0.036)	(0.0019)		(0.0024)
Avg. Median Year:		0.063	0.064		0.0001	-0.0003
Technological$_{ft}$		(0.029)	(0.031)		(0.0017)	(0.0017)
Avg. Median Year:			0.021			0.0048
Other Occupations$_{ft}$			(0.030)			(0.0017)
Number of Observations	2675	1933	1392	2411	1737	1278
Numb. of Ads (thousand)	65	59	58	70	63	61

Table 8: Relationships among job vintages of different occupation types and firm characteristics

Notes: An observation is a combination of a two-year-period and firm. Within each regression, our specification includes two-year-period fixed effects, 2-digit industry fixed effects, and the fraction of job ads within each 2-digit SOC occupation.

tus, and year of entry and exit from Compustat. Being publicly traded, transitioning into publicly traded status is primarily due to newer vintage organizational jobs. Newer vintage organizational jobs (but not other types of jobs) are associated with firms that more recently entered publicly traded status, and are far form exiting the universe of publicly traded firms. Conversely, firms with newer vintage technological jobs are *more* likely to exit the Compustat database. So, while technological job vintages are primarily associated with sales growth and R&D intensity (both of these variables are measured only for the set of publicly traded firms), organizational job vintages are more closely related going or remaining public.

In Table 10, we shift the focus of our analysis to privately held firms. We find that survival (which, again, we proxy for using placing ads in future periods) is lower for firms that post newer vintage technological jobs.

4.3 Narratives

To close this section, and with the goal of making our statistical analysis on job vintage measures more concrete, we present vignettes of firms which placed ads for newly emerging and soon-to-be disappearing job titles. The first two of these examples describe the ads placed by Digital Equipment Corporation (DEC) and Wang Laboratories. DEC was a leader in the manufacturer of computers in the 1960s; Wang Laboratories developed new word processing equipment in the 1970s. To succeed in these newly emerging industries, these two firms required employees whose skills complemented their core capabilities. Finally, we provide examples of the types of job ads placed by less innovative firms.

To guide these narratives, Figure 2 plots the relationship between firms' sales growth

Dep. Variable	(1)	(2)	(3)	(4)	(5)	(6)
	Publicly Traded			Soon to be Publicly Traded		
Avg. Median Year: Organizational$_{ft}$	0.005		0.005	0.003		0.006
	(0.002)		(0.002)	(0.001)		(0.002)
Avg. Median Year: Technological$_{ft}$		0.001	0.000		0.001	0.001
		(0.002)	(0.002)		(0.002)	(0.002)
Avg. Median Year: Other Occupations$_{ft}$			0.006			0.003
			(0.002)			(0.001)
Number of Observations	10416	6353	4313	7328	4201	2797
Numb. of Ads (thousand)	233	187	177	153	117	110
	(7)	(8)	(9)	(10)	(11)	(12)
Dep. Variable	Entry Year to Compustat			Exit Year from Compustat		
Avg. Median Year: Organizational$_{ft}$	0.132		0.148	0.227		0.233
	(0.028)		(0.036)	(0.076)		(0.102)
Avg. Median Year: Technological$_{ft}$		-0.010	-0.011		-0.188	-0.204
		(0.029)	(0.030)		(0.086)	(0.096)
Avg. Median Year: Other Occupations$_{ft}$			0.039			0.127
			(0.028)			(0.080)
Number of Observations	2672	1929	1389	2672	1929	1389
Numb. of Ads (thousand)	75	66	64	75	66	64

Table 9: Relationships among job vintages of different occupation types and publicly traded status

Notes: An observation is a combination of a two-year-period and firm. Within each regression, our specification includes two-year-period fixed effects and the fraction of job ads within each 2-digit SOC occupation. In columns (7) through (12) our regressions also include 2-digit industry fixed effects.

Dep. Variable	(1)	(2)	(3)	(4)	(5)	(6)
	Survive Five Years			Survive Ten Years		
Avg. Median Year: Organizational$_{ft}$	0.0008		-0.0008	0.0002		0.0000
	(0.0012)		(0.0014)	(0.0015)		(0.0021)
Avg. Median Year: Technological$_{ft}$		-0.0013	-0.0009		-0.0035	-0.0033
		(0.0009)	(0.010)		(0.0016)	(0.017)
Avg. Median Year: Other Occupations$_{ft}$			0.0023			-0.0011
			(0.0015)			(0.0022)
Number of Observations	7552	4338	2880	7318	4248	2834
Numb. of Ads (thousand)	156	119	113	154	118	112

Table 10: Relationships among job vintages of different occupation types and firm survival

Notes: An observation is a combination of a two-year-period and firm. Within each regression, our specification includes two-year-period fixed effects and the fraction of job ads within each 2-digit SOC occupation.

and their average vintages (according to the Avg. Median Year variable). To facilitate comparison across points in time, for each firm-year ($f - t$) observation we compute the average vintage of firms' posted ads relative to the average among all firms posting in year t. To reduce the effect of sampling uncertainty, we average observations across 5-year periods. For instance, the point corresponding to "DEC, 1970-74" indicates that DEC's sales growth increased by $\exp(1.58) = 487$ percent between the early 1970s and late 1970s and that the ads which DEC posted were of 4.5 years newer vintage compared to the other firms posting ads in the early 1970s. Consistent with Table 2, Figure 2 demonstrates that firms which post newer vintage jobs tend to have faster than average revenue growth.

Our first example, DEC, a manufacturer of computers since 1959, had its initial commercial success in 1965 with its PDP-8. "The PDP-8's success, and the minicomputer phenomenon it spawned, was due to a convergence of a number of factors, including performance, storage, packaging, and price." (Ceruzzi, 2003, p. 130)[14] To develop these new products, DEC hired workers in a number of emerging jobs, primarily but not limited to technological occupations. In the early 1970s, DEC posted multiple ads for *Programmer Analysts, Software Support Specialists,* and *Systems Programmer* jobs (all falling within the technological occupation codes) and *Computer Sales Representatives* (an organizational occupation). All four of these job titles emerged after 1960. While DEC placed a larger-than-average fraction of its ads for technological jobs (in the late 1960s, 45 percent of DEC's ads were in technological occupations, more than double the sample average), it did still post a substantial number of ads in organizational occupations. Moreover, both the technological and organizational job ads that DEC posted were of relatively new vintage — *Systems Programmer* is a relatively new vintage technological job title at the time; *Marketing Managers, and Credit Analysts* (also posted by DEC) were relatively new vintage organizational jobs at the time. Of course, DEC placed ads not only for newly emerging job titles, but also placed multiple ads for *Designers*, *Managers*, and *Manufacturing Engineers*; all three of these job titles had been in existence for multiple decades prior. Nevertheless, compared to the other firms within our sample, DEC's ads were of newer vintage: Among the ads it posted in the late 1960s, the average job title vintage (as measured by the Avg. Year of Emergence$_{ft}$ variable) was over 5 years newer than other ads posted by publicly traded firms. And, consistent with our earlier statistical analysis from Section 4.1, DECs hiring practices were associated with faster growth. With the success of its PDP-8, DEC grew tremendously. First publicly traded in 1967, DEC's sales from $289 million in that year, to $871 million in 1970, $7.41

[14] About the long-lasting impact of DEC, Ceruzzi further writes: "The modest appearance of the PDP-8 concealed the magnitude of the forces it set into motion.. The mini showed that with the right packaging, price, and above all, a more direct way for users to gain access to computers, whole new markets would open up." (Ceruzzi, 2003, p. 141)

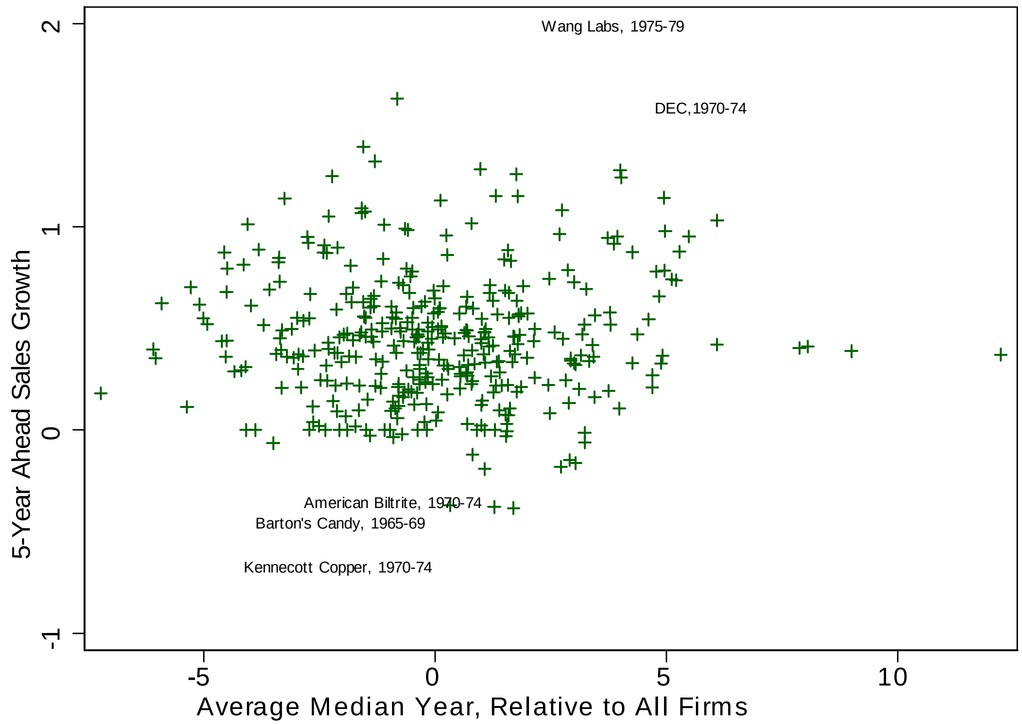

Figure 2: Relationship between firm vintages and sales growth.
Notes: For each publicly-traded firm we compute the five-year average of two variables: (i) the sales growth in the subsequent five years, and (ii) the "Avg. Median Year", relative to the other ads posted in the given year. Within this plot, we depict only the set of firm-five-year-period pairs for which the firm posted at least 40 ads within the given five-year period. We spell out the name and give the five-year period of the firms that are the focus of this subsection. American Biltrite posted 64 ads between 1970 and 1974. Barton's Candy posted 51 ads between 1965 and 1969. DEC, and Kennecott Copper posted 62 ads, 210 ads, and 48 in the same period. Wang Labs posted 204 ads between 1975 and 1979. The correlation between the two variables on this plot, including all firm-five-year period observations and weighting by the number of ads, is 0.19.

billion in 1980. (All dollar figures are stated relative to the 2017 CPI.)

Our second comes from later in the 1970s — Wang Laboratories. Initially a manufacturer of electronic calculators, Wang Laboratories successfully transitioned into designing and manufacturing word processing equipment in the 1970s.[15] Wang Labs' employment increased by nearly a factor of 6 — from $422 million to $2.40 billion — in the five years following its 1976 initial public offering. As one of the leaders in this new market, Wang Labs posted vacancies for a number of emerging occupations, including for *Market Support*

[15] Ceruzzi writes of Wang Laboratories: "Wang had an astute sense of knowing when to get out of one market and into a new one about to open up. Dr. Wang was, in fact, a conservative engineer who understood the technology of his company's products and who valued his company's independence... Wang engineers found out first of all what office people wanted. They realized that many users of word-processing equipment were terrified of losing a day's work by the inadvertent pressing of the wrong key. ... Wang's engineers came up with a design that would make such a loss nearly impossible." (Ceruzzi, 2003, pp 255-256)

Representatives, *Field Service Technicians*, and *Programmer Analysts.* These workers complement Wang's core businesses. Programmer Analysts were necessary to construct and improve upon Wang Labs' key software and hardware. Field Service Technicians were employed to help Wang Labs' customers install, use, and maintain this relatively new word processing equipment. As with DEC, Wang Labs posted ads for both organizational and technological jobs, with a greater-than-average share of technological jobs, and with both types of jobs being of relatively new vintage.

At the other end of the spectrum from DEC and Wang Labs are firms like American Biltrite, Barton's Candy, and Kennecott Copper. A manufacturer of flooring and rubber, American Biltrite's 1970s were a period of turmoil: It's employment fell from 5000 in 1976 to less than 2000 by 1981.[16] Within this period, the vacancies posted by American Biltrite were overrepresented in disappearing occupations. It posted multiple ads for *Keypunch Operators* and for *Clerk Typists* throughout the 1970s. Like American Biltrite, Kennecott Copper and Barton's Candy had periods of exceptionally slow growth (for Kennecott this would be in the early 1970s, for Barton's Candy in the late 1960s) in conjunction with a preponderance of advertisements in disappearing job titles. In addition to *Clerk Typists* ads, Barton's Candy posted ads for *Stenographer Typist* and *Switchboard Operator* positions in the late 1960s; Kennecott Copper posted ads for *Mail Clerk*, *Rate Clerk*, and *Typist* ads. All of these job titles correspond to for disappearing work practices.

To emphasize, we do not wish to imply that the management of American Biltrite, Barton's Candy, or Kennecott Copper were acting against their firms' best interests by posting vacancies for job titles which would disappear in the short-to-medium term. While it's definitely possible that these firms' slow adaptation to new work practices is leading to future distress, it's also possible that other sources of distress may cause firms to refrain from searching for applicants in emerging occupations (Brown and Matsa, 2016). What is clear, however, is that American Biltrite, Barton's Candy, and Kennecott Copper, through posting ads for disappearing job titles, are conveying that it is still profitable to bring in workers to complement their existing firm capabilities (otherwise they would not be advertising). At the same time, these firms are also demonstrating that the cost of adopting to new technologies and production processes — those technologies and processes which could be implemented by workers in newer vintage job titles — outweigh the long-term benefits that the firm could accrue by implementing them.

[16] The *Wall Street Journal* wrote at the time: "Last year, American Biltrite Inc. reported a $12.2 million loss, closed four plants, laid off more than a quarter of its workers and eliminated dividends. Management termed 1977 'the most difficult year in the company's 70 years.'" Bulkeley (1978)

5 Conclusion

Drawing on newspaper vacancy postings from 1940 to 2000, this paper documents that firms hiring for emerging jobs perform well while those that hire for disappearing jobs perform poorly. Emerging job titles correspond to high-skilled, information and communication technology intensive work and are introduced by fast-growing R&D intensive firms. In short, emerging job titles reflect new technologies and modes of production. Disappearing jobs on the other hand correspond to dying technologies and organizational practices, and the firms searching for such workers ultimately perform poorly or disappear.

Distinguishing between emerging jobs that are technical in nature, versus ones that relate to business and operations presents additional nuance. The results suggest that firms hiring at the technological frontier perform better, but in the longer term, being savvy and hiring at the forefront of business aspects is key to going public and surviving. Inevitably, even the most innovative product a firm develops can be replicated to be standardized and eventually becomes obsolete. Firms can try to maintain a competitive edge by investing on the technology frontier, but as organizations grow in size it becomes difficult to incentivize risk taking. Given this, it appears that as firms mature, the successful ones hire for novel, emerging non-technology workers who facilitate the survival of the company (versus the commercialization of a product) in an ever changing business environment.

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A Additional Details on Processing the Job Ad Text

In this appendix, drawing on Atalay, Phongthiengtham, Sotelo, and Tannenbaum (2018, 2019), we outline the steps necessary to extract task and technology mentions from the job ad text. Then, we describe the way in which we extract information about the entity posting the ad, how we extract the posted salary, and how we compute the vintage of each job title. Parts of the first two paragraphs of this appendix quote directly from (Atalay, Phongthiengtham, Sotelo, and Tannenbaum, 2018, p. 50).

The original newspapers were digitized by ProQuest using an Optical Character Recognition (OCR) technology. We briefly describe the steps we take to transform this digitized text into a structured database. To begin, the raw text does not distinguish between job ads and other types of advertisements. Hence, in a first step, we apply a machine learning algorithm to determine which pages of advertisements are job ads. In a second step we extract, from each advertisement, words that refer to tasks the new hire is expected to perform and technologies that will be used on the job. So that we may link the text-based data to occupation-level variables in the decennial census, including wages, education, and demographic variables, the procedure also finds the Standard Occupation Classification (SOC) code corresponding to each job title.

To extract job tasks from the text, we use a mapping between words and task categories based on Spitz-Oener (2006). The five tasks are *nonroutine analytic*, *nonroutine interactive*, *nonroutine manual*, *routine cognitive*, and *routine analytic*.[17] To retrieve a more complete measure of these task groups, and because we do not want our analysis to be sensitive to trends in word usage or meaning, we adopt a machine-learning algorithm called the *continuous bag of words* to define a set of synonyms for each of our task-related words. The idea of the algorithm is that two words that share surrounding words in the text are likely to be synonyms. For example, one of the words corresponding to the nonroutine analytic task is *researching*. The continuous bag of words method uses the corpus of job ad the text itself to find synonyms of researching; these synonyms include *interpreting*, *investigating*, *reviewing*, etc. In our analysis, we include the union of my original task-related words (from footnote 17) with the these synonyms identified from the continuous bag of words model. as words mapping to the nonroutine analytic task, which limits the sensitivity of my analysis to variations in diction over time. In addition to the five task measures, we search for mentions of 48 individual technologies which are mentioned at various points of the 1940.[18]

New to this paper, we extract information on the entity which posted the vacancy posting. To do so, we begin by searching within the job ad text for three types of strings: First, we search for strings which indicate a firm name: "agency," "agcy," "associates," "as-

[17] We use the mapping of words to tasks as described in Atalay, Phongthiengtham, Sotelo, and Tannenbaum (2019). For convenience, we list the taxonomy again here: 1) nonroutine analytic: analyze, analyzing, design, designing, devising rule, evaluate, evaluating, interpreting rule, plan, planning, research, researching, sketch, sketching; 2) nonroutine interactive: advertise, advertising, advise, advising, buying, coordinate, coordinating, entertain, entertaining, lobby, lobbying, managing, negotiate, negotiating, organize, organizing, presentation, presentations, presenting, purchase, sell, selling, teaching; 3) nonroutine manual: accommodate, accommodating, accommodation, renovate, renovating, repair, repairing, restore, restoring, service, serving; 4) routine cognitive: bookkeeping, calculate, calculating, correcting, corrections, measurement, measuring; 5) routine manual: control, controlling, equip, equipment, equipping, operate, operating.

[18] These 48 technologies are APL, BAL, CAD, CICS, CNC, COBOL, C++, DB2, DOS, EDP, FORTRAN, FoxPro, HTML, IBM 360, IBM 370, IBM 5520, IBM RPG, Java, JCL, LAN, Lotus 123, Lotus Notes, MS Excel, MS PowerPoint, MS Word, MVS, Novell, Oracle, PASCAL, Point of Sale, PowerBuilder, Quark, Sabre, SQL, Sybase, TCP, TSO, UNIVAC, Unix, VAX, Visual Basic, VMS, VSAM, Vydec, WordPerfect, Xerox 630, Xerox 800, and Xerox 860.

soc," "co," "company," "corp," "corporation," "inc," "incorporated", "llc," and "personnel." Second, we search for a 7-digit number (which would indicate a phone number) that does not begin with "0" or a "1" (in the United States phone numbers do not begin with these digits) and does not have a "$" preceding it. Third, we search for strings that indicate an address: "ave," "st," "42nd," "bway," "wall," and "box." Having extracted strings that fit one these three forms, we next manually combine common firm names from the first list of strings. For example, for any job title which contains the string "3m company" or "minnesota mining manufacturing co," we assign the posting firm to be the "3m company." Next, for each commonly appearing phone number, we examine whether (within the same set of ads) there is a firm name which also uniquely appears. If so, for any ads for which this phone number appears but the firm name does not, we then assign the firm name from the set of ads for which the commonly appearing phone number appears with a firm name. (For instance, suppose there is some phone number — e.g., 555-5555 — appearing in ads for the 3m company. In any ads for which 555-5555 appears but the 3m company does not, we re-assign the firm name to be the 3m company.) In instances in which commonly appearing phone numbers do not map to firm names, we retain the phone number as the identifier of the posting entity. In a final step, for ads for which a firm name is not yet assigned, we then manually assign firm names based on addresses. For instance, "341 madison 44 st" appears as an address for which we had previously identified the Taft Agency as the posting firm. Thus, for ads for which we observe "341 madison 44 st" but not the posting firm, we re-assign the posting firm to be the Taft Agency. As a result of this procedure, we are able to ascertain the identity of the entity posting the ad for 14 percent of the ads.

Finally, we extract information on the salary which the applicant would be paid. To do so, we search for groups of strings indicating a salary. A main difficulty to contend with is that certain employers quote salaries on an annual basis, others on a weekly or hourly basis. With this in mind, we search for the following sets of strings to indicate an annual salary:

- "to x 000," "$ x 000," where x is a number between 5 and 39, between 40 and 100 (searching in multiples of 5), and between 100 and 250 (searching in multiples of 25);
- "to x 500," $ x 500," where x is a number between 5 and 14
- " xk ," where x is a number between 8 and 39, between 40 and 100 (searching in multiples of 5), and between 100 and 250 (searching in multiples of 25).

Within these searches, we restrict attention to ads in which there is at most one dollar sign (since multiple dollar signs may indicate multiple possible salaries.) Further, we search for additional common strings, indicating other possible salaries:

- the string "$ 8 10 000," for instance, would indicate a salary range of eight to ten thousand dollars. From this, we record a salary of "$10,000"

Additionally, we search for weekly salaries. To do so, we search for strings of the form:

- "$ x y" where x is a number between 40 and 160 (in multiples of 5) and y is equal to $x+5$ or $x+10$. In instances like this, the firm is indicating a salary range of x to y per week. For jobs like this, we record the number y to be the salary.

- "$ x wk," "$ x per wk," "$ x week," or "$ x per week" for x between 20 and 300 (in multiples of 5).

Also within these searches, we restrict attention to ads in which there is at most one dollar sign. Further, we search for additional common strings, for example:"

- the string "$ 35 50," " $ 55 70," "$ 80 100" to indicate weekly salaries of $50, $70, or $100.

Finally, we search for hourly wages by searching for stings of the form "x yz hr," "x yz per hr," or "x yz per hour" where x, y, and z are numbers. Among the 5.0 million ads within the benchmark sample, we are able to ascertain a posted salary for 4 percent of the ads.

An Example

Figures 3 and 4 illustrate the performance of our text-processing algorithm. Figure 3 presents a portion of a page of ads from the *New York Times*, the version which was digitized by ProQuest and delivered to us. Figure 4 presents the results of our text-processing procedure. The Atalay, Phongthiengtham, Sotelo, and Tannenbaum (2019) algorithm first identifies the boundaries between individual ads, then the job title from each ad, and then maps each job title to a Standard Occupational Classification (SOC) occupation code. Further, we have extracted task-related words: the ad for a *Transportation Advertising Supervisor* includes three mentions of nonroutine interactive tasks — advertising, media, and sales — and a single mention of a nonroutine analytic tasks: creating. Within two other ads, we identify two other mentions of nonroutine analytic tasks: research in the first ad and evaluation in the final ad. New, relative to Atalay, Phongthiengtham, Sotelo, and Tannenbaum (2019), we identify a salary of $7,000 in the first advertisement and "Mobil Oil Company" and "United Aircraft Corporation" in the fourth and final advertisements. So, our procedure

TIMES ACCOUNTANTS Due to staff promotions, openings have developed in our Cost and Auditing Divisions of parent company. We are looking for men with 2 to 5 years of experience with a large public accounting firm. Good opportunities for growth. Excellent salary. Send resume to Personnel Department Johnson &Johnson. New Brunswick, New Jersey MECHANICAL ENGINEER Specialist In selection of pumps, compressors &general mechanical equipment. 4 te 6 yrs exp. with pump mfr.. engineering contractor. o or public utility, etc. o . . Good starting salary o . Ercellent conditions ark Area BOX 219, Large New England sheet metal fabricating plant manufacturing extensive line of InstItutional furniture has good opportunity for Methods Engineer with comprehensive knowledge of ope,ations and layout. Include resume and salary. requirements. X7548 TIMES u RESUMES PRINTED S3.50 lst5Goiviesfnciudiiw type. Si ch - add. 100 copIes. I Add 35c to mall ord (P1AE) Open DiSh td6 P.M. DAY The PRESS 42Wust 33 SI4E6Y.C. OX 5.3658 Major Oil Company Needs A TRANSPORTATION ADVERTISING SUPERVISOR With Specific experience in creating advertising for: truck-bus, aviation, marine or construction industries. Understanding of advertising media, creative functions, agency relationships and organization procedures. College degree with a background in advertising and sales promotion. Versatility, initiative and a good personality. Some knowledge of the, petroleum requirements and their application to the transportation industries desirable. OPPORTUNITY FOR ADVANCEMENT ? by letter only, submitting detailed resume of education, experience and salary requirements. Socony Mobil Oil Company, Inc. 150 East 42 Street, N. Y. (at Lexington) PERFORMANCE ENGINEERS Aircraft &Space Vehicle Systems Evaluation Diversified projects include the evaluation of advanced propulsion concepts for subsonic, hypersonic and space vehicles in terms of system performance capabilities. Sustained program with excellent support from services from the largest industrial computing efforts by experienced component specialists. Minimum qualifications for these positions include a M.S. degree in aeronautical engineering plus 3 related experience. UNITED AIRCRAFT CORPORATION 400 Main Street . East Hartford, Conn. Please write to Mr. W. M. Walsh RESEARCH LABORATORIES

Figure 3: Unprocessed Ads Partial from the April 10, 1960 *New York Times*
Notes: The figure panel presents the digitized text from a portion of a page of display ads. This figure is a reproduction of Figure 1 of Atalay, Phongthiengtham, Sotelo, and Tannenbaum (2019) .

identifies useful information related to the tasks workers are expected to perform, the firms who are posting the ads, the posted salaries, and the job titles. However, the measurement error associated with our algorithm is appreciable: most likely *Buyer* should be the job title associated with the first ad. (In a later stage, we delete job titles, like *Senior*, that appear to refer solely to a personal noun or adjective, and not to a job or career individual and not a job. Other common examples which appear in the text, but which we eliminate, are *Boys, Boys Girls,* and *Veterans.*) Moreover, our algorithm could not recognize the boundary between the job ad for a *Mechanical Engineer* and that for a *Methods Engineer.*[19]

B Additional Calculations Related to Section 3.2

B.1 Top Job Titles by Vintage

In this appendix, we presents a sample of the jobs which appeared and disappeared within each decade of our sample period. The first panel lists the job titles which disappeared by the end of the 1940s. According to the panel, the *Lens Grinder*, *Radio Instructor*, *Christmas Card Salesperson*, and *Fluorescent Salesperson* are mentioned primarily in the first decade of the sample. In later decades, job titles with the word "stenography" or "stenographer" tend to disappear in the 1960s and 1970s; job titles with the word "keypunch" or "typist" tend to disappear in the 1970s and 1980s. Conversely, job titles including "word processing" or "word processor" tend to appear in the 1970s; "telemarketing" in the 1980s; and "web"-related job titles in the 1990s.

B.2 Comparison to Lin (2011)

In this appendix, as a validation exercise, we compare job titles' appearance and disappearance — based our dataset of newspaper vacancy postings — to Lin (2011)'s measures of new work. Lin (2011) compares different versions of the Dictionary of Occupational Titles and the U.S. Census Classified Indexes — from the 1965, 1977, 1991 Dictionary of Occupational Titles; and the 1990 and 2000 Classified Indexes — to identify new job titles. We link the job title is the newspaper text to the job titles which Lin (2011) has compiled.[20] we categorize the matched job titles into four groups, based on their presence in different

[19] Furthermore, our initial parsing algorithm incorrectly affixes the word "Times" to the job title "Times Accountant." In a later stage, we manually remove such extraneous words at the beginning and end of each job title; see Appendix A.

[20] We apply a fuzzy matching algorithm, using STATA's *matchit* command; see Raffo (2015). We link job titles for which the Jaccard similarity between the newspaper-baed job title and the DOT job title is greater than 0.85. The succeeding results in this section are similar with exact string matching.

SENIOR [[151143]] Leading Mid-Manhattan engineering company seeks Senior Buyer with minimum 3 purchasing experience in research and development field handling electronic corn . Capable of rea in blueprints SALARY TO $7,000 Send Complete Resume to. KK 105

TIMES ACCOUNTANT [[132011]] Due to staff promotions, openings have developed in our Cost and Auditing Divisions of parent company. We are looking for men with 2 to 5 years of experience with a large public accounting firm. Good opportunities for growth. Excellent salary. Send resume to Personnel Department Johnson &Johnson. New Brunswick, New Jersey

MECHANICAL ENGINEER [[172141]] Specialist In selection of pumps, compressors &general mechanical equipment. 4 te 6 yrs exp. with pump mfr.. engineering contractor. o or public utility, etc. o . . Good starting salary o . Ercellent conditions ark Area BOX 219, Large New England sheet metal fabricating plant manufacturing extensive line of InstItutional furniture has good opportunity for Methods Engineer with comprehensive knowledge of ope,ations and layout. Include resume and salary. requirements. X7548 TIMES u RESUMES PRINTED S3.50 lst5Goiviesfnciudiiw type. Si ch - add. 100 copIes. I Add 35c to mall ord (P1AE) Open DiSh td6 P.M. DAY The PRESS 42Wust 33 SI4E6Y.C. OX 5.3658 Major Oil Company Needs A

TRANSPORTATION ADVERTISING SUPERVISOR [[531031]] With Specific experience in creating advertising for: truck-bus, aviation, marine or construction industries. Understanding of advertising media, creative functions, agency relationships and organization procedures. College degree with a background in advertising and sales promotion. Versatility, initiative and a good personality. Some knowledge of the, petroleum requirements and their application to the transportation industries desirable. OPPORTUNITY FOR ADVANCEMENT ? by letter only, submitting detailed resume of education, experience and salary requirements. Socony Mobil Oil Company, Inc. 150 East 42 Street, N. Y. (at Lexington)

with specific experience in creating advertising for truck-bus , aviation , marine or construction industries . understanding of advertising media , creative functions , agency relationships and organization procedures . college degree with a background in advertising and sales promotion . versatility , initiative and a good personality . some knowledge of the , petroleum requirements and their application to the transportation industries desirable . opportunity for advancement ? by letter only , submitting detailed resume of education , experience and salary requirements . so cony Mobil oil company , inc . 150 east 42 street , n . y .

PERFORMANCE ENGINEER [[173029]] Aircraft &Space Vehicle Systems Evaluation Diversified projects include the evaluation of advanced propulsion concepts for subsonic, hypersonic and space vehicles in terms of system performance capabilities. Sustained program with excellent support from services from the largest industrial computing efforts by experienced component specialists. Minimum qualifications for these positions include a M.S. degree in aeronautical engineering plus 3 related experience. UNITED AIRCRAFT CORPORATION 400 Main Street . East Hartford, Conn. Please write to Mr. W. M. Walsh RESEARCH LABORATORIES

Figure 4: Processed text from the April 10, 1960 *New York Times*.
Notes: We identify five ads from the unprocessed text. The job title that we have identified, located at the beginning of each ad, is written in bold. We draw a diamond around the salary which we have identified within the first job ad, and a rectangle around the firm names we have identified within the third and fifth ads. We highlight nonroutine analytic and interactive tasks: "creating," "evaluation," and "research" refer to nonroutine analytic tasks; "advertising," "media," and "sales" refer to nonroutine interactive tasks." We also search for nonroutine manual, routine cognitive, and routine manual tasks. There are no mentions of these tasks within these ads. The six-digit code in square brackets refers to the SOC code which we have identified: 132011 is the code for Accountants and Auditors; 172141is the code for Mechanical Engineers; 531031 is the code for First-Line Supervisors of Transportation and Material-Moving Machine and Vehicle Operators; and 173029 is the code for Engineering Technicians.

Disappearing Job Titles		Emerging Job Titles	
$v_j^{0.99}$ ∈1940-49		$v_j^{0.01}$ ∈1950-1959	
1	lens grinder	1	administrative assistant
2	radio instructor	2	programmer
3	christmas card salesperson	3	legal secretary
4	fluorescent salesperson	4	management trainee
5	national tech	5	systems analyst
$v_j^{0.99}$ ∈1950-1959		$v_j^{0.01}$ ∈1960-1969	
1	soda dispenser	1	programmer analyst
2	millinery designer	2	computer operator
3	buyer wants contd	3	marketing manager
4	long distance telephone operator	4	product manager
5	testy sales	5	medical center
$v_j^{0.99}$ ∈1960-1969		$v_j^{0.01}$ ∈1970-1979	
1	house worker	1	paralegal
2	bookkeeper stenographer	2	typesetter
3	dental mechanic	3	word processing
4	alteration hand	4	word processor
5	collector salesperson	5	stock broker trainee
$v_j^{0.99}$ ∈1970-1979		$v_j^{0.01}$ ∈1980-1989	
1	stenographer	1	telemarketer
2	stenographer typist	2	hiv aid
3	secretary stenographer	3	line cook
4	office boy	4	broker trainee
5	comptometer operator	5	medical biller
$v_j^{0.99}$ ∈1980-1989		$v_j^{0.01}$ ∈1990-2000	
1	clerk typist	1	power builder
2	draftsman	2	client server
3	statistical typist	3	web developer
4	biller typist	4	web master
5	keypunch operator	5	actor auditions

Table 11: Top receding and emerging job titles.

Notes: Each panel contains job titles which have $v_j^{0.99}$ or $v_j^{0.01}$ in a given decade. Within each panel, we list the top five job titles, measured according to the number of ads in which the job title appears within the 1940 to 2000 sample.

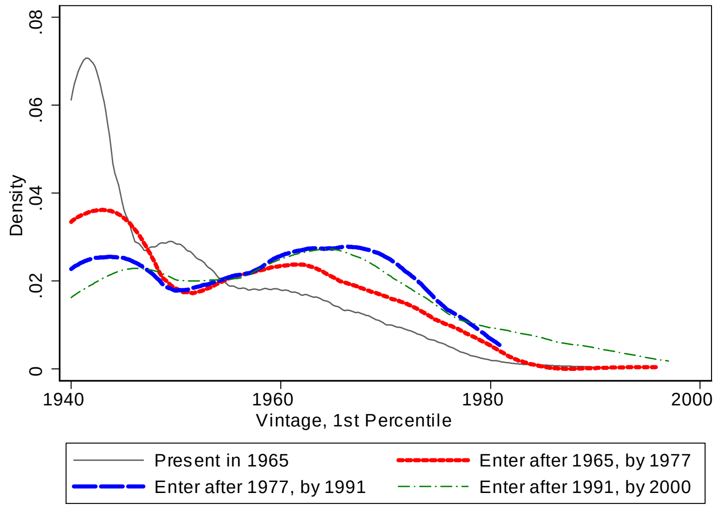

Figure 5: Density of entry dates.
Notes: This figure presents the density of entry dates, as measured within the newspaper vacancy postings, for four groups of job titles. The four groups are based on the dates in which they first appear within the Dictionary of Occupational Titles or the Census Classified Index.

vintages of the DOT data: (i) job titles which were already present in the 1965 version of the DOT; (ii) job titles which first appeared in the 1977 DOT; (iii) job titles which first appeared in the 1991 DOT; and (iv) job titles which first appeared in the 2000 Census Classified Index list of job titles. Among the newspaper job titles which could be matched to Lin (2011)'s compiled dataset, there are 4320 job titles in group (i), 195 job titles in group (ii), 158 job titles in group (iii), and 185 job titles in group (iv). Figure 5 compares the distribution of entry dates across these four groups. Reassuringly, the newspaper-based entry dates align, at least directionally, with those in Lin (2011)'s analysis. The average entering vintage of newspaper job titles in group (i) is 3.0 years earlier than in group (ii), 6.2 years earlier than in group (iii), and (iv) 9.6 years earlier than in group (iv). However, there are a substantial number of group (iii) and (iv) job titles — job titles which first appear in either the 1991 DOT list or the 2000 Classified Index — which were present in early-year newspaper job ads. For instance, the *Assistant Broker, Assistant Buyer, and Assistant Store Manager* all first appeared in the 2000 Classified Index, but had 10 percent of their newspaper job ads appear before 1965.