Emerging and Disappearing Work, Thriving and Declining Firms

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Abstract

We propose a new measure of firms' technology adoption, based on the types of employees they seek. We construct firm-year level measures of emerging and disappearing work using ads posted between 1940 and 2000 in the *Boston Globe*, *New York Times*, and *Wall Street Journal*. 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 all firms, those which post ads for emerging work are more likely survive and, for privately held firms, are more likely to go public in the future. We develop a model – consistent with these patterns – with incumbent job vintage upgrading and firm entry and exit. Our estimated model indicates that 55 percent of upgrading occurs through the entry margin, with incumbents accounting for the remaining 45 percent.

1 Introduction

How do new technologies displace old ones? This is a foundational question in the fields of economic growth, innovation, and management. At the firm level, the decision to adopt a new technology in lieu of an existing one is risky, but with potentially high rewards. In the aggregate, early adopters provide informational spillovers, paving the path for broad adoption and productivity enhancements.

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Unfortunately, comprehensive economy-wide firm-level measures of technology adoption have been difficult to come by.[1] In this paper, we provide a new angle to measuring the types of technologies that firms utilize. We hypothesize that technologies are embedded in work practices, namely in the types of workers and skills for which firms hire. We use data on firms' job postings to learn about the technologies they are adopting, then assess the sources of new technology adoption.

As we will demonstrate, there is substantial churn in the types of work performed within and across firms. To provide one example, in the mid-twentieth century the Typist job title was one of the most frequently occurring titles in the United States labor market. By the 1980s, typewriters were almost completely phased out of the workplace and few jobs carried the Typist title. Instead, around this time, job titles like Word Processor were newly emerging. Other technology-specific or function-specific jobs titles like Comptometer Operator, Stenographer, and Soda Dispenser were also once common but have since disappeared. Conversely, certain jobs which were common at the close of the twentieth century—including Paralegal, LAN Administrator, and Systems Analyst—were virtually unknown fifty years earlier. Each of these newly emerging job tittle is associated with a new technology – some combination of techniques, processes, and administrative activities involved in the production of goods and services – which firms adopt.

In this paper, we ask: What are the sources of this churn, this creative destruction? Specifically, to what extent do new firms account for industries' technology upgrading? We begin our study by constructing new measures of the vintages of work that firms seek in their employees. Our measures are built using job ads posted in the *Boston Globe*, *New York Times*, and *Wall Street Journal* over the 1940-2000 period. For each ad, we retrieve the job title; and, for each job title we introduce measures of its relative newness. The intent of our job vintage measures is to capture how "new" or "old" a job title is relative to the date at which it is being hired for, with the broader goal of inferring the vintage of the technology that firms utilize. Take the example from before of the Comptometer Operator job title. While relatively common in the 1940s through 1960s, this job title had disappeared by 1980. Thus, a firm hiring for a Comptometer Operator in 1940 may have been ahead of its time in hiring for such work, while a firm doing the same thing in the 1970s would be hiring for outmoded work. More generally, the "newness" of a job title corresponds to various qualities that are typically indicative of technologies that are close to the frontier.[2]

[1] We discuss previous attempts at measurement in Section 2.

[2] As Lin (2011) writes: "new job titles represent new combinations of activities or techniques that have emerged in the labor market in response to the application of new information, technologies, or 'recipes' to production." (p. 554) We validate our measure of job title vintages in three ways. First, we demonstrate that our job title vintage measures align with those developed in Lin (2011). Second, we show that newer vintage

We next document that firms with new or emerging job titles are more innovative and better performing than firms posting ads for old or disappearing job titles. Among publicly traded firms, those posting vacancies pertaining to new work have higher future sales growth and are more R&D intensive: A one standard deviation increase in our job title vintage measure corresponds to 4 percent faster sales growth over the next five years, 6 percent faster sales growth over the next ten years, and R&D expenditures to sales ratios that are (among the sample of firms with positive R&D expenditures) higher by 11 log points. Among all firms, those posting ads with newer vintage job titles are more likely to be publicly traded and have (somewhat) more highly cited patents. Finally, young firms post ads for newer vintage work, while firms that post ads for soon-to-be disappearing job titles are more likely to exit the in the near future. While, reassuringly, our new job-title-based measure of firm innovativeness correlates with existing measure, a key advantage to our measure is that can be constructed for any firm that posts job ads, and is not limited to publicly traded firms or to industries in which patenting is prevalent.[3]

Having established that our job title vintage measure relates to firm outcomes in consequential and sensible ways, we apply our measure to quantify the extent to which new firms account for technology upgrading. To do so, we construct a model of the two sources of technology upgrading, either through firm entry and exit or through incumbents investing in updating the technology vintage they employ. In our model, we assume that consumers' tastes shift as time progresses: Consumers prefer to purchase only varieties produced by technologies sufficiently close to the frontier. Firms with obsolete technologies, by assumption, exit the industry. To maintain their position in the market, incumbents forego current-period profits to (probabilistically) by incurring the cost to upgrade to the frontier technology.[4] In addition to incumbent firms technology upgrading, upgrading may occur through the entry of new firms: They pay a sunk entry cost to enter with a relatively-new technology vintage. Beyond technology vintages, firms differ in their age (the date at which they first entered the economy) and their total factor productivity (exogenously given,

jobs tend to have higher posted salaries and have college degree requirements more frequently. And, third, newer vintage jobs more frequently require that prospective employees be familiar with new information and communication technologies. In other words, job title vintages have practical and meaningful implications for the type of work firms are hiring for, and for the technological intensity of that work.

[3]Patenting is heavily concentrated in a small number of industries. These differences reflect not only differences in industries' innovativeness but also differences across products in the extent to which patents confer intellectual property protection. As Argente, Baslandze, Hanley, and Moreira (2020) report in their study of the consumer packaged good sector, many new product introducts are not associated with patent filings.

[4]In reality, the obsolescence that induces firm exit may reflect not only changing consumer tastes, but also the introduction of newer, lower-cost technologies. The key features of our setup are that new technologies exogenously appear, that firms face a costly decision of whether to adapt to the new technology, and that lack of new technology adoption for a sufficiently long period of time leads to firm exit.

determined upon entry).

According to our model, higher fixed entry costs (relative to the cost of incumbent technology upgrading) implies that the value of having a frontier technology is high, which in turn corresponds to a high benefit that incumbents accrue from technology upgrading. With higher fixed entry costs, there are many high productivity firms who both survive to be long-lived and have the newest vintage job titles. In the cross-section, older firms have frontier technologies. And with high fixed costs, there is substantially more dispersion in firms' ages than in technology vintages. In contrast, small fixed entry costs correspond to a correlation between age and distance to the frontier that is close to 1 and similar levels of dispersion in firm ages and job title vintages.

We estimate our model via a simulated method of moments procedure using data on firms' ages, job vintages, and sales. We find that approximately 55 percent of technology upgrading occurs through the entry margin when firms are weighted according to their sales, more than 90 percent when firms are weighted equally. That is to say, both entry and exit and incumbents costly investments are important channels of new technology adoption. Finally, we explore heterogeneity across industries in the relative importance of the entry margin. In manufacturing, where firms tend to be younger, on average, the net entry margin accounts for a higher fraction of technology upgrading.

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, macroeconomics and labor economics. Section 3 then discusses the source data, our measurement of job title vintages, and 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 develops and estimates our model of technology upgrading. Section 6 concludes.[5]

2 Related Literature

Our paper builds on and contributes to at least three interconnecting literatures within economics: one which decomposes the sources of innovation between entrants and incumbents, one which studies the diffusion of new technologies, and one which uses job titles to learn about technological change.

Regarding the first of these literatures, building on Klette and Kortum (2004), a recent literature has evaluated the role that entrants play in propelling technological progress

[5] In the appendices, we outline our measurement of posted salaries, the identity of the posting firm, and job titles (Appendix A), assess the representativeness of our sample, (Appendix B), present supplementary empirical analyses (Appendix C), and discuss the simulation of our model (Appendix D).

through Schumpeterian product innovation; see, also, the review article by Aghion, Akcigit, and Howitt (2014). More recently, Akcigit and Kerr (2018) and Garcia-Macia, Hsieh, and Klenow (2019) each construct and estimate models whereby both entrants and incumbents can engage in product — and, in Garcia-Macia, Hsieh, and Klenow (2019), process — innovation. Both find that entrants account for approximately one-quarter of aggregate productivity growth; see Table 6 of Akcigit and Kerr (2018) and Table 5 of Garcia-Macia, Hsieh, and Klenow (2019). We also consider a model in which entrants and incumbents account for technological change. The scope of our analysis is narrower than that in Akcigit and Kerr (2018) and Garcia-Macia, Hsieh, and Klenow (2019): We are not seeking to provide a comprehensive decomposition of aggregate TFP growth,only to understand the replacement of old work practices for new ones. The advantage of this narrow scope is that it allows us to focus on the type of technical change we can most directly measure: the vintages of technologies that firms adopt.

Our work also relates to a voluminous work on the introduction and diffusion of new technologies. Empirical works either examine industry or aggregate data on the adoption rates of a wide variety of new technologies (Gort and Klepper (1982); Comin and Hobijn (2004, 2010); Anzoategui, Comin, Gertler, and Martinez (2019)); or examines the firm- or individual-level adoption rates of a single or handful of technologies (Henderson and Clark (1990); Conley and Udry (2010)). Papers that develop models consistent with this literature include Jovanovic and Lach (1989), Chari and Hopenhayn (1991), Jovanovic and MacDonald (1994), and Jovanovic and Yatsenko (2012). Relative to the empirical portion of the literature on technology diffusion, our firm-level measures are comparable across a wide swath technologies and industries. Relative to the theoretical portion, our contribution is to develop a heterogeneous firm model in which both the net entry and incumbent upgrading margin can play a role.[6]

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. In more recent work, Atalay, Phongthiengtham, Sotelo, and Tannenbaum (2020) compare new versus old job titles and their task content. We find that, even within similar occupational groups, newer job titles are more non-routine task intensive. Relative to these papers, the key novelty in our work is to link firms to the vintage of job titles in their vacancies.[7]

[6] Among the cited papers, only Jovanovic and Lach (1989) contains technology upgrading through firm entry and exit. In their paper, firms are homogeneous within each cohort and cannot upgrading the vintage of their capital after they enter.

[7] Like us, Deming and Kahn (2018) relate firm characteristics to the content in their job ads. They find

In sum, our paper makes two key advances over the existing literature. First, we introduce new measures of technology adoption at the firm-year level, over a long time horizon and across a wide swath of firms. Second, we develop a model of technology adoption to answer a new substantive question.

3 Data and Measurement Issues

3.1 Data Source and Variables

Our 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, 2020) 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.[8] The dataset contains 9.26 million 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 — appears 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 20 distinct ads through the sample period. With this restriction, the benchmark dataset contains 5.21 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

that firms posting ads containing a greater frequency of mentions of social and cognitive skills also tend to pay higher wages, have higher labor productivity, and are more likely to be publicly traded. Deming and Noray (2019) explore emerging and disappearing work, not through ads' job titles but instead through skill requirements mentioned in the ads' bodies. For each occupation, they measure the extent to which skill requirements change over time. They find that the life-cycle wage profile is flatter in fast-changing occupations, in particular in STEM-related jobs.

[8] 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 (2020) 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 agencies (e.g., the American Community Survey).

the name of a firm: "agency," "agcy," "associate," "associates," "assoc," "co," "company," "corp," "corporation," "inc," "incorporated," "llc," and "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 5.21 million ads which will form the basis for the analysis, below, we could extract information on the posting party for 712 thousand ads. For these 712 thousand ads, we could identify only a phone number or address for 163 thousand ads. For 296 thousand ads, the posting party we identified was an employment agency. For the remaining 252 thousand ads, we have identified an employer who is placing the ad on its own behalf. Among these, for 205 thousand ads, we have identified the firm's 2-digit industry code, and the entry date for 195 thousand ads.[9] We could match the identity of the posting party to the Compustat dataset in 82 thousand ads, and to the NBER Patenting database for 38 thousand ads. 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 5.21 million ads that form the base sample, we could extract information on the posted salary for 190 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. In Appendix B, we examine the extent to which the ads for which we can identify the employer is representative of the broader sample of newspaper job ads.

3.2 Measuring Job Title Vintages

For each job title j, we compute a triple of statistics, summarizing the dates at which the job title was introduced to 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 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 (2020), p. 29) Our main analysis centers around $v_j^{0.01}$ as our measure for the year in which job title j entered the dataset, $v_j^{0.99}$ as our measure

[9] We have identified these pieces of information through manual online searches.

for year in which job title j left the dataset, and $v_j^{0.50}$ as capturing the average vintage of job title j.[10]

Figure 1 illustrates the construction of these percentiles for 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 three vertical lines. For the *Comptometer Operator* job title, the 1st, 50th, and 99th percentile years in which the title was mentioned are 1941, 1952, and 1974. In other words, $\left(v_j^{0.01}, v_j^{0.50}, v_j^{0.99}\right) = (1941, 1952, 1974)$ for $j =$*Comptometer Operator*. Analogously, for $j =$Figure Clerk $v_j^{0.01} = 1950$, $v_j^{0.50} = 1970$, and $v_j^{0.99} = 1988$.

As a validation exercise of our job title vintage measures, we compare job titles' appearance — based on 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 in our newspaper text to the job titles which Lin (2011) has compiled.[11] We categorize the matched job titles into four groups, based on their presence in different vintages of the DOT and Census 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 4734 job titles in group (i), 172 job titles in group (ii), 117 job titles in group (iii), and 161 job titles in group (iv). Figure 2 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

[10] Our measures of the years of job title entry and exit correspond to the $p = 1^{\text{st}}$ and $p = 99^{\text{th}}$ 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 observations. On the other hand, choosing a p closer to 0.50 yields a measure less directly related to entry or exit, instead capturing an overall measure of the years in which the job title appears.

[11] 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.

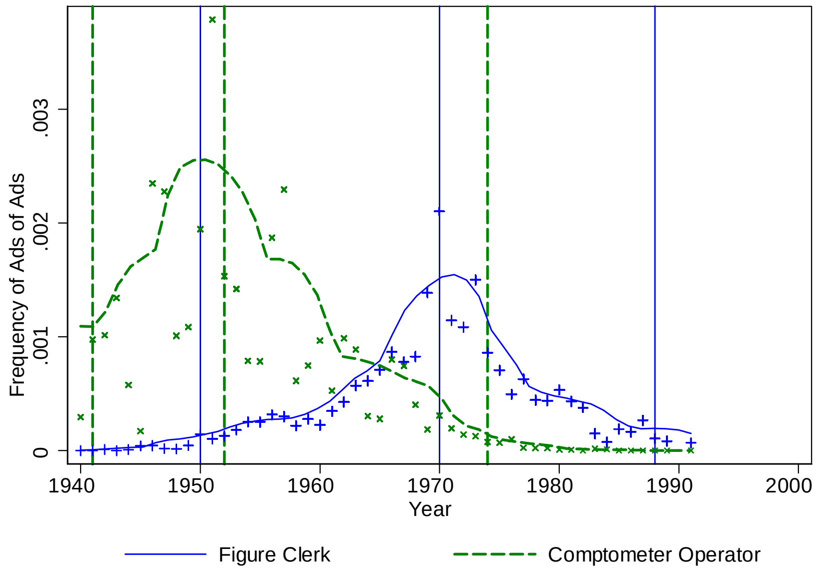

Figure 1: Job title frequencies.

Notes: We plot the frequency of two individual job titles for each year between 1940 and 2000. The vertical lines depict $v_j^{0.01}$, $v_j^{0.50}$, 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.

entering vintage of newspaper job titles in group (i) is 4.4 years earlier than in group (ii), 9.2 years earlier than in group (iii), and 11.1 years earlier than in group (iv).[12] 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 Census Classified Index — which were present in early-year newspaper job ads. For instance, the *Assistant Buyer, General Superintendent*, and *Portrait Photographer* job titles all first appeared in the 2000 Census Classified Index, but had 10 percent of their newspaper job ads appear before 1965.

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

[12]In these averages, each job title is weighted equally. Weighting job titles by the number of times they appear in our dataset, the three differences — between group (i) versus groups (ii), (iii), and (iv) — are 4.0 years, 5.6 years, and 8.7 years, respectively.

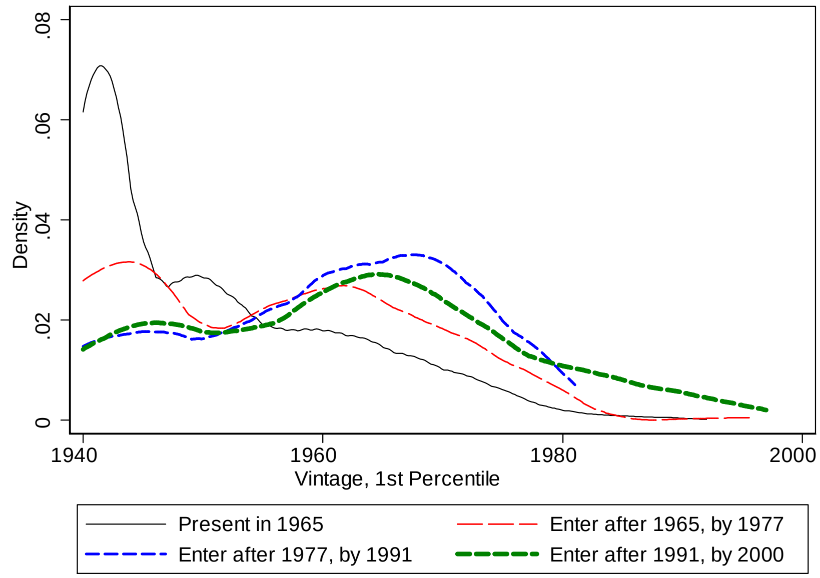

Figure 2: Density of entry dates.
Notes: This figure presents the density of entry dates, as measured within the newspaper vacancy postings, for four groups of job titles. The four groups are based on the dates in which they first appear within the Dictionary of Occupational Titles or the Census Classified Index.

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:

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

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 hourly 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 decade increase in job title vintages is associated with a 1.9 log point increase ($\approx 10 \cdot (0.0015 + 0.0004)$) 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 (4) broadly align with Greenwood and Yorukoglu (1997) and Caselli (1999). There, the authors argue that skilled individuals have a comparative advantage in using new technologies.[13]

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:

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

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 0.10 standard deviation increase job ads' technology mentions, a 0.02 standard deviation increase in undergraduate degree mentions, and no difference in graduate degree mentions.[14]

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

4 Job Title Vintages and Firm Characteristics

Having demonstrated that job title vintages are correlated with other work characteristics indicative of innovative activity, we provide a first statistical analysis of the relationship between average job vintages among the ads placed by each firm and the firm's current and future performance.

Our initial set of regressions compares firm-level sales, productivity, R&D intensity,

[13] In principle, the relationship between salaries and job title vintages may be negative. Employers who need to hire workers for a disappearing job may need to pay a compensating differential to attract workers in a job that is at risk of not existing in the near future. The fact that we find a positive relationship between salary and job title vintage indicates that these compensating differentials — generating differences in wages for workers of a given skill level — generate less variation in wages than the forces highlighted by Greenwood and Yorukoglu (1997) and Caselli (1999).

[14] 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 8.93 mentions (per 1000 job ad words). So, a one decade increase in $v_j^{0.01}$ and $v_j^{0.99}$ translates to a $0.89 (\approx 10 \cdot (0.040 + 0.049))$ increase in technology mentions per 1000 ad words, equivalent to $0.10 (\approx 0.89/8.93)$ standard deviations of our ICT measure.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	—— Log Salary ——				Technology	
Year	0.0018	0.0015	0.0003	0.0020	0.106	0.040
of Emergence	(0.0002)	(0.0002)	(0.0004)	(0.0002)	(0.001)	(0.001)
Year	0.0026	0.0004	-0.0003	0.0034	0.078	0.049
of Disappearance	(0.0002)	(0.0002)	(0.0003)	(0.0004)	(0.001)	(0.001)
Mean of Dep. Variable					1.56	
Std. Dev. of Dep. Variable	0.64		0.52	1.11	8.93	
N (thousand)	180		97	84	2,174	
SOC F.E.	No	Yes	Yes	Yes	No	Yes
Sample	1940-2000		1940-1969	—— 1970-2000 ——		
	(7)	(8)	(9)	(10)	(11)	(12)
Dep. Variable	—— Undergraduate Degree ——				Graduate Degree	
Year	0.0118	0.0063	0.0106	0.0060	-0.0028	-0.0077
of Emergence	(0.0003)	(0.0003)	(0.0008)	(0.0004)	(0.0005)	(0.0005)
Year	0.0074	0.0033	0.0038	0.0062	0.0327	0.0100
of Disappearance	(0.0002)	(0.0003)	(0.0003)	(0.0007)	(0.0004)	(0.0004)
Mean of Dep. Variable	0.56		0.44	0.73	1.66	
Std. Dev. of Dep. Variable	4.14		3.70	4.64	7.62	
N (thousand)	5,043		2870	2174	5,043	
SOC F.E.	No	Yes	Yes	Yes	No	Yes
Sample	1940-2000		1940-1969	1970-2000	1940-2000	

Table 1: Relationship between job title vintages, salaries, technology measures, and educational requirements.

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. SOC F.E. refers to fixed effects for the 4-digit SOC of each ad.

future sales growth, and future productivity growth to measures of job title vintages. For the ads that a firm i places in year t, we average over the job vintage measures that we introduced in the previous section:

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

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

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

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

Our comparisons are based on the following regression specification:

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

Within Equation 6, x_{it} represents either firm-year level labor productivity, R&D intensity, future sales growth, or labor productivity growth; β_t are year-level fixed effects; and, X_{it} are firm-level controls. These include the the logarithm of the firm's book value of total assets, employment, and revenues in year t; the fraction of the firm's ads that are in each 2-digit occupation code in year t; and 1-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 and productivity growth on the other hand. To emphasize, by including year-level fixed effects (β_t), our comparisons between job title vintages and other firm characteristics exploit variation across firms within a given year. Throughout this section, we weight observations by the number of job ads posted by firm i in year t.[15]

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 a weak, positive relationship between firms' revenues and their job title vintages. According to column (2),

[15] Most, but not all, of the results presented in this section are similar in unweighted specifications. We highlight differences when they occur, below. Appendix C.2 collects the analogues of Tables 2 to 6 where observations are weighted equally.

for example, a 3.74 year increase job title vintages (equivalent to the across-firm, within-year standard deviation of the job title vintage measure) is associated with a 7 percent increase in sales. The relationship between vintage and revenues is no longer statistically significant once one controls for the shares of firm-year job ads that are posted in each 2-digit occupation code (column 4).[16] Columns (5) through (8) assess the relationships among job vintages and labor productivity. For the most part, the relationship between job title vintage and productivity is not statistically significant. Columns (9) through (16) indicate that there is stark increasing relationship between firms' job vintage measures and R&D intensity. Among the set of firms with positive R&D expenditures, a one-standard deviation increase in job title vintages is associated with a 11 percent increase in R&D intensity (column 10). Among the broader set of firms, an equivalent increase in job title vintages is associated with R&D intensity that is 58 log points higher (column 14). Controlling for both industry and occupational mix attenuates these estimated relationships for broader of firms (compare column 14 to column 16) but not for firms with positive R&D expenditures (compare columns 10 and 12). In sum, Table 2 suggests, first, that firms posting for newer vintage work are (perhaps) somewhat more productive and larger, and that, second, newer vintage job titles are correlated with R&D intensity.

So, Table 2 indicates that new work practices are a marker of innovative activity. Is our job title vintage measure, then, predictive of future firm outcomes? Table 3 addresses this question. In the first eight columns, we relate firms' job posting behavior in year t to their sales growth up to year $t+5$ (columns 1 through 4) or year $t+10$ (columns 5 through 8). Across all specifications, firms that post ads for newer vintage jobs grow faster. A one standard deviation increase in our Avg. Median Year$_{ijt}$ measure corresponds to 4 percent faster growth over the next five years, 6 percent over the next decade. (While the regressions in Table 3 omit R&D intensity as a covariate, the results would be nearly unchanged with this variable's inclusion.) In these first eight columns, our sample includes only firms that survive up to five years (in the first four columns) or ten years (columns 5 through 8). Since omission from the sample largely corresponds to firms that have poor outcomes, the first eight columns likely understate the relationship between growth and job title vintages. In columns (9) through (16), we account for this sample selection problem. Here, we show that the association between sales growth and job title vintages is stronger (columns 9 through 12) and that firms posting for newer work practices also tend to experience an increase in labor productivity (columns 13 through 16).

[16] In unweighted specifications, firms that post ads for *older* vintage job titles are larger and more productive. However, with the exception of the estimate of β_1 in the specification corresponding to column (3), these relationships are not statistically significant.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Variable		——	$\log(y_{it})$	——		——	$\log(lp_{it})$	——
Avg. Year of Emergence$_{it}$			0.006				-0.0002	
			(0.012)				(0.0020)	
Avg. Median Year$_{it}$	0.032	0.018		-0.014	0.0003	0.0011		–0.0021
	(0.009)	(0.009)		(0.009)	(0.0020)	(0.0017)		(0.0020)
Avg. Year of Disappearance$_{it}$			0.011				0.0123	
			(0.015)				(0.0043)	
Other Controls	None	Industry F.E.		Industry F.E. SOC Shares	None	Industry F.E.		Industry F.E. SOC Shares
R^2	0.088	0.142	0.185	0.185	0.815	0.863	0.868	0.867
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Dep. Variable		——	$\log(\text{R\&D}_{it}/y_{it})$	——		——	$\log(\text{R\&D}_{it}/y_{it})$	——
Avg. Year of Emergence$_{it}$			0.033				0.032	
			(0.007)				(0.034)	
Avg. Median Year$_{it}$	0.041	0.030		0.031	0.264	0.154		0.055
	(0.007)	(0.006)		(0.006)	(0.039)	(0.035)		(0.034)
Avg. Year of Disappearance$_{it}$			0.004				-0.083	
			(0.011)				(0.064)	
Other Controls	None	Industry F.E.		Industry F.E. SOC Shares	None	Industry F.E.		Industry F.E. SOC Shares
R^2	0.261	0.340	0.375	0.376	0.300	0.418	0.442	0.441

Table 2: Relationship between job title vintage, sales, productivity, and R&D intensity.
Notes: The "SOC Shares" 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. In columns (5)-(16), the regressions also include log(assets) and log(employment) as covariates. In columns (9)-(12), only firm-year observations with positive R&D expenditures are included. In columns (13)-(16), we impute missing log(R&D to sales ratios) using the minimum value in our sample. The sample in columns (1)-(4) includes 5005 firm-year observations corresponding to 81 thousand job ads; the sample in columns (5)-(8) and (13)-(16) includes 4830 observations, corresponding to 78 thousand job ads; the sample in columns (9)-(12) includes 2520 observations, corresponding to 38 thousand job ads.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Variable			$\log(y_{i,t+5}/y_{it})$				$\log(y_{i,t+10}/y_{it})$	
Avg. Year of Emergence$_{it}$			0.006				0.012	
			(0.003)				(0.004)	
Avg. Median Year$_{it}$	0.013	0.010		0.008	0.020	0.016		0.014
	(0.002)	(0.002)		(0.002)	(0.004)	(0.003)		(0.003)
Avg. Year of Disappearance$_{it}$			0.002				0.002	
			(0.003)				(0.004)	
Other Controls	None	Industry F.E.		Industry F.E. SOC Shares	None	Industry F.E.		Industry F.E. SOC Shares
R^2	0.206	0.241	0.247	0.250	0.225	0.261	0.273	0.276
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Dep. Variable			$\log(y_{i,t+10}/y_{it})$				$\log(lp_{i,t+10}/lp_{it})$	
Avg. Year of Emergence$_{it}$			0.024				0.016	
			(0.006)				(0.005)	
Avg. Median Year$_{it}$	0.040	0.026		0.019	0.022	0.013		0.012
	(0.004)	(0.004)		(0.005)	(0.004)	(0.004)		(0.004)
Avg. Year of Disappearance$_{it}$			0.007				0.005	
			(0.006)				(0.006)	
Other Controls	None	Industry F.E.		Industry F.E. SOC Shares	None	Industry F.E.		Industry F.E. SOC Shares
R^2	0.054	0.066	0.068	0.068	0.054	0.066	0.068	0.068

Table 3: Relationship between job title vintage, sales growth, and labor productivity growth.

Notes: The "SOC Shares" refer to variables which measure the share of ads, within the firm-year observation, corresponding to each 2-digit SOC code. The employment, sales, and asset data are computed using data from Compustat. In each regression, log(assets) and log(employment) are included as covariates. In columns (1)-(8) the sample includes only firm-year observations which are present in the Compustat database five or ten years later. In columns (9)-(16), we estimate a censored (Tobit) regression, imputing the value for sales and labor productivity growth to be equal to -2 for firms that exit the Compustat sample, and setting the lower threshold at this point. The sample in columns (1)-(4) includes 4368 firm-year observations, corresponding to 75 thousand job ads. The sample in columns (5)-(8) includes 3897 firm-year observations, corresponding to 71 thousand job ads. The sample in columns (9)-(16) includes 4830 fim-year observations, corresponding to 78 thousand job ads.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable		Publicly Traded			Publicly Traded Within 10 Years?	
Avg. Year of Emergence$_{it}$		0.0067 (0.0019)			0.0072 (0.0021)	
Avg. Median Year$_{it}$	0.0128 (0.0015)		0.0053 (0.0016)	0.0033 (0.0015)		0.0042 (0.0014)
Avg. Year of Disappearance$_{it}$		0.0043 (0.0025)			0.0021 (0.0019)	
Other Controls	Industry F.E.		Industry F.E. SOC Shares	Industry F.E.		Industry F.E. SOC Shares
R^2	0.219	0.248	0.248	0.127	0.137	0.136

Table 4: Relationship between job title vintage and firms' publicly traded status.
Notes: The "SOC Shares" refer to variables which measure the share of ads, within the firm-year observation, corresponding to each 2-digit SOC code. Within columns (4)-(6), the dependent variable "Publicly Traded within 10 Years" 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. The sample in columns (1)-(3) includes 14257 firm-year observations, corresponding to 205 thousand job ads. The sample in columns (4)-(6) includes 8770 firm-year observations, corresponding to 121 thousand ads.

Tables 4, 5, and 6 expand our analysis beyond publicly traded firms. To begin, we compare job vintages for publicly-traded firms and privately held firms.[17] According to the first three columns of Table 4, publicly traded firms tend to post newer vintage jobs. In the next 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_{it} is now an indicator variable equal to 1 if firm i becomes publicly traded on or before year $t + 10$. Privately held firms which post ads for new work are substantially more likely to become publicly held in the future: A one standard deviation increase in our job vintage measure is associated with a 1.4 percentage point increase (off of a base of 14.7 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 new work practices relates positively to firm outcomes, given that it is the most successful private firms (or startups) that are typically the ones to go public.

In Table 5 we compare our job vintage measure to a measure of innovative activity applicable to both privately held and publicly traded firms: patenting. We match firm

[17] 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.

names in our newspaper dataset to those in the NBER Patenting Database.[18] According to this table, firms that post ads with newer vintage job titles tend patent more frequently (columns 1-4) and have patents that are more patent citations (columns 5-8). In the final eight columns of Table 5, we assess the relationship between patenting and job vintages, now conditioning on R&D intensity. In part because the sample is now restricted to publicly traded firms, the estimated relationships in columns (9) to (16) are substantially weaker than those in columns (1) to (8). In sum, firms with more patents and more highly cited patents post ads for newer vintage work, but this relationship potentially reflects underlying differences in firms' R&D intensity and in industry composition.

Do younger firms post ads for newer work practices? And does posting ads for soon-to-be disappearing jobs predict exit from the market? Table 6 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 dependent variable equal to year in which the firm first entered, or exited from, the market. (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.) We apply two differing measures of entry and exit, each with their own advantages and disadvantages. In the first six columns, our measures of entry and exit are collected from hand web searching, while in the final six columns our entry and exit measure capture appearance or disappearance from publicly traded status (measured as presence or absence in the Compustat database). The hand-collected data have the advantage of capturing true entry and exit — not simply entry and exit from publicly traded status — and span a wider set of firms, but have the disadvantage of relying on our own judgement in certain instances.[19] Columns (1) and (4) indicate that firms with one-decade newer job title vintages tend to be younger by 6.9 years (column 1 of Table 6) and survive for an additional 1.8 years (column 4), though the latter estimate is not significantly different from zero. In terms of entry to or exit from publicly traded status (columns 7 through 12), the results are somewhat weaker for the date of entry and somewhat stronger

[18] We use the database that covers patenting activity between 1963 and 1999, downloaded from `https://data.nber.org/patents/pat63_99.txt.`

For firms that we could not find a name match, we set the patent or citation counts to be equal to zero, assuming that the reason that the lack of the match reflects no actual patenting activity by the firm that is posting the job ad. The results in Table 5 are similar when restricting to firm-year observations for which we could match firm names across the newspaper and NBER patenting databases.

[19] There are at least two complications in assigning a date of exit. First, struggling firms tend to be acquired (at, potentially, a price much lower than the book value of its assets) as opposed to shutting down completely. We treat being acquired as exit from the market, but acknowledge that this choice is open to debate. Second, struggling firms will declare bankruptcy, potentially reorganizing at the same point in time, but then continue under the same name. We treat these events as also exiting from the industry, again realizing that alternate choices may also be defensible.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Variable	——	$\log\left(\text{patents}_{i,t}+1\right)$		——	——	$\log\left(\text{citations}_{i,t}+1\right)$		——
Avg. Year of Emergence$_{it}$			0.013				0.019	
			(0.006)				(0.009)	
Avg. Median Year$_{it}$	0.027	0.026		0.001	0.043	0.041		0.005
	(0.005)	(0.005)		(0.005)	(0.007)	(0.007)		(0.007)
Avg. Year of Disappearance$_{it}$			0.005				-0.007	
			(0.005)				(0.007)	
Other Controls	None	Industry F.E.		Industry F.E. SOC Shares	None	Industry F.E.		Industry F.E. SOC Shares
R^2	0.253	0.324	0.363	0.363	0.314	0.363	0.393	0.392

	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Dep. Variable	——	$\log\left(\text{patents}_{i,t}+1\right)$		——	——	$\log\left(\text{citations}_{i,t}+1\right)$		——
Avg. Year of Emergence$_{it}$			0.021				0.030	
			(0.009)				(0.012)	
Avg. Median Year$_{it}$	0.022	0.001		-0.014	0.035	0.008		-0.014
	(0.008)	(0.008)		(0.008)	(0.010)	(0.010)		(0.010)
Avg. Year of Disappearance$_{it}$			-0.023				-0.029	
			(0.011)				(0.015)	
$\log\left(\text{R\&D}_{it}/y_{it}\right)$	0.104	0.079	0.07	0.075	0.148	0.114	0.106	0.106
	(0.007)	(0.008)	(0.008)	(0.008)	(0.009)	(0.010)	(0.010)	(0.010)
Other Controls	None	Industry F.E.		Industry F.E. SOC Shares	None	Industry F.E.		Industry F.E. SOC Shares
R^2	0.639	0.678	0.689	0.688	0.658	0.695	0.706	0.705

Table 5: Relationship between job vintage and patenting activity.

Notes: The "SOC Shares" refer to variables which measure the share of ads, within the firm-year observation, corresponding to each 2-digit SOC code. In addition to the listed explanatory variables, the regressions in columns (9)-(16) include log(employment) and log(assets) as covariates. Within columns (1)-(8), the sample includes 14257 firm-year observations, corresponding to 205 thousand job ads. In columns (9)-(16), the sample includes 4830 firm-year observations, corresponding to 78 thousand job ads.

for the date of exit.

To sum up, while firms which post ads for newer vintage jobs are only slightly (if at all) larger and 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.[20]

5 A Model of Technology Upgrading

We consider a model of technology upgrading and obsolescence consistent with the patterns documented in the previous section. In our economy, there are two margins through which technologies of different vintages evolve: entrants (who, on average, posses newer vintage technologies) replacing exiting firms, and incumbent firms upgrading their technologies. Within our framework, technology upgrading is necessary to keep pace with consumers' evolving preferences.[21] The goal of our model is to use the joint distribution of firms' ages, their technology vintages, and their revenues to infer the relative costs of entry and incumbent technology upgrading.

5.1 Setup

Consider a continuous time economy, where time is indexed by t. Each firm i produces a single variety. There is a representative consumer who has preferences over the different varieties consumed:

$$U_\tau = \int_\tau^\infty e^{-r(t-\tau)} \log\left(C_t\right) dt \quad \text{, where}$$
$$C_t = \left[\int_{i:v(i)\in[t,t+1]} c_t\left(i\right)^{(\eta-1)/\eta} di\right]^{\eta/(\eta-1)} \quad .$$

[20]Complementing these exercises, in Appendix C.3 we illustrate through narrative examples the relationship between firm performance and job title vintages. We compare DEC and Wang Laboratories — two firms which, in the 1960s and 1970s respectively advertised for newly emerging work — to American Biltrite, and Bethlehem Steel — two firms which sought out employees to perform jobs which were soon to disappear.

[21]An alternate formulation with similar observable implications would involve (i) new technologies appearing that, once adopted, allow firms to produce at a reduced marginal cost, and (ii) overhead costs of production. As in our model, firms which fail to update their technology eventually would be eventually forced to exit the industry.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable		Entry Year			Exit/Acquisition Year	
Avg. Year of Emergence$_{it}$		0.521 (0.153)			0.279 (0.183)	
Avg. Median Year$_{it}$	0.694 (0.124)		0.621 (0.1120)	0.178 (0.109)		-0.027 (0.125)
Avg. Year of Disappearance$_{it}$		0.401 (0.179)			-0.068 (0.143)	
Other Controls	Industry F.E.		Industry F.E. SOC Shares	Industry F.E.		Industry F.E. SOC Shares
R^2	0.253	0.286	0.287	0.039	0.044	0.044
	(7)	(8)	(9)	(10)	(11)	(12)
Dep. Variable		Entry Year to Compustat			Exit Year from Compustat	
Avg. Year of Emergence$_{it}$		0.290 (0.059)			0.523 (0.103)	
Avg. Median Year$_{it}$	0.227 (0.044)		0.279 (0.051)	0.686 (0.073)		0.394 (0.082)
Avg. Year of Disappearance$_{it}$		0.169 (0.077)			0.650 (0.105)	
Other Controls	Industry F.E.		Industry F.E. SOC Shares	Industry F.E.		Industry F.E. SOC Shares
R^2	0.066	0.070	0.070	0.026	0.032	0.031

Table 6: Relationship between job vintage, entry year, and exit year.

Notes: The "SOC Shares" refer to variables which measure the share of ads, within the firm-year observation, corresponding to each 2-digit SOC code. The sample in columns (1)-(3) includes 13202 firm-year observations, corresponding to 195 thousand job ads. The sample in columns (4)-(6) includes 5922 firm-year observations, corresponding to 137 thousand ads. In columns (7)-(12), we apply a tobit regression to account for censoring; the R^2 refers to the pseudo-R^2. The sample in these columns includes 4856 firm-year observations, corresponding to 79 thousand job ads. 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 4865 firm-year observations, the entry year is equal to 1950 for 2121 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 1511 observations.

Consumers' tastes exogenously change over time: At time t, consumers seek to purchase varieties that have *vintage* v between t and $t+1$. We assume that firms with vintage less than t are forced to exit the industry. We refer to vintages less than or equal to t as "obsolete," vintage $t+1$ as the "frontier" and $k = t+1-v$ as the "distance to the frontier technology."

Upon entry, firms are endowed with a production technology vintage $v \in [t, t+1]$. Without further innovation (described below), firms' vintages are held fixed over time. In addition to their vintage, firms are endowed (upon entry) a productivity level $z > 0$, which allows it to transform l units of labor into $z \cdot l$ units of output. This z is held fixed for each firm throughout its life-cycle. Both entrants' productivity, z, and their initial technology vintage, v, are random variables, independent both within and across firms. Furthermore, assume that the density of entrants' productivity levels, $g(z)$, and the density of entrants' distances to the frontier, $h(k)$, are both time invariant.

We assume that firms engage in monopolistic competition with their competitors. Given this, incumbent firms' variable profits are given by:

$$\pi(i) = \pi_0 \cdot z(i)^{\eta-1}, \tag{7}$$

where π_0 is a constant, independent of k and z.[22]

Firms may update the vintage of their technology via costly innovation. We assume that firms that pay flow costs equal to $\frac{\kappa}{2}\lambda^2$ to have a stochastic arrival rate of vintage updating (to the frontier vintage) equal to λ. (This assumption is consistent with our previously documented finding that R&D expenditures and newer job vintages are correlated.) Further, we use r to denote the firms' discount rate. And, finally, we assume that firms exogenously exit at a rate δ per model period. Allowing for exogenous exit in our setup is necessary since, without it, firms with sufficiently high z would never allow their vintage to become obsolete. With $\delta = 0$, our model would struggle to fit the (finite) dispersion of firms' ages.

In our model, a single period refers to the length of time that it takes for a frontier technology to become obsolete. Let T refer to the number of years corresponding to a period in our model. With r^A denoting the annual discount rate and δ^A the annual probability of exogenous exit, $r = (1+r)^T - 1 \approx Tr^A$ and $\delta \approx T\delta^A$.

Given our assumptions and definitions, the continuous-time Bellman equation, for a

[22] Let the wage serve as the numeraire in our economy. Thus, the marginal cost of production for a firm with productivity z equals $\frac{1}{z}$. Given the assumption of monopolistic competition and CES preferences, firms with productivity z set a price equal to $\frac{\eta}{\eta-1}\frac{1}{z}$. Let $\tilde{g}(z)$ denote the mass of productivity z surviving firms; and let $P \equiv \left[\int_0^\infty \frac{\eta}{\eta-1} z^{\eta-1} \tilde{g}(z)\, dz\right]^{1/(1-\eta)}$ denote the ideal price index. With these definitions, a firm with productivity z will have revenues equal to $\pi_0 \cdot z^{\eta-1}$, where $\pi_0 \equiv P^\eta \cdot C \cdot (\eta-1)^{\eta-1} \cdot \eta^{-\eta}$. Both P and C will depend on the rate at which firms enter and the average productivity of surviving firms.

firm with exogenous TFP z and distance to the frontier k is given by:

$$(r+\delta)\cdot V(k,z)=\max_{\lambda\geq 0}\pi_0\cdot z^{\eta-1}-\frac{\kappa}{2}\lambda^2+\lambda\cdot[V(0,z)-V(k,z)]+V'(k,z)\quad . \tag{8}$$

Firms equate the marginal cost of innovating to the marginal gain from updating an old vintage to the frontier:

$$\kappa\cdot\lambda=V(0,z)-V(k,z)\quad . \tag{9}$$

The right-hand side is increasing in k and increasing in z. First, conditional on z, firms within near obsolete vintages have most to gain from updating their vintage: Since V is decreasing in k, λ is increasing in k. Second, firms with higher exogenous productivity earn higher variable profits and thus have more to gain from keeping up-to-date vintages. Since the cost of innovation is unrelated to z, λ is increasing in z.

Our assumption that firms with obsolete vintage technologies are forced to exit the industry implies that

$$V(1,z)=0 \tag{10}$$

for each z.

Applying Equation 9, the solution to Equation 8 is given by:

$$(r+\delta)\cdot V(k,z)=\alpha\cdot z^{\sigma-1}+\frac{1}{2\kappa}\left[V(0,z)-V(k,z)\right]^2+V'(k,z)\quad . \tag{11}$$

Finally, we use a free-entry condition to (implicitly) determine the number of entrants in each industry. Let f denote the sunk cost that entrants must pay to enter the industry. We assume that entrants enter up to the point at which f equals the expected value of having distance to the frontier k and TFP z:

$$f=\int_0^\infty\left[\int_0^1 V(k,z)\,h(k)\,dk\right]g(z)\,dz\quad . \tag{12}$$

Since there are no additional fixed costs, after entering all firms throughout the z distribution produce until the point at which their vintage becomes obsolete.

We consider a stationary equilibrium. In this equilibrium, firms set prices to maximize their static profits (footnote 22), choose innovation rates λ to maximize the present discounted value of their firm (Equation 9), and enter up to the point that the sunk entry cost equals the expected value of owning a firm with TFP z and distance to the frontier k (Equation 12).

5.2 Characterization and Estimation

To parameterize our model, we compare the joint distribution of firms' log sales, their distances to the frontier, and their age (the difference between the current period and the date at which the firm originally entered) in our model simulations and in our data. In our application, we parameterize z to be drawn from a log-normal$\left(-\frac{1}{2}\sigma^2, \sigma^2\right)$ distribution; and let the density of entrants' distance to the frontier be given by $h(k) = \beta \cdot (1-k)^{\beta-1}$ for $\beta \geq 0$ and $k \in [0,1]$.[23] We set $\kappa = 1$, $r^A = 0.02$, $\delta^A = 0.001$ and $\eta = 3$.[24]

With the goal of explaining how our model is identified, we plot model moments for different combinations of f, T, β, and σ. In the top left panel of Figure 3, we explore the correlations among age, distance to the frontier, and sales for various values of the sunk entry cost; here we set $(f, T, \beta, \sigma) = (0.060, 15.10, 2.06, 0.606)$.[25] When entry is relatively free, the increase in value that incumbent firms would earn from updating their technology is relatively low. As a result, incumbent firm technology updating is infrequent, and technologies' vintages are linked tightly to the date at which the firm entered. On the other hand, for high values of f, incumbent firms invest heavily in updating their technologies. Given the selection of which firms update (high z firms update their vintages particularly intensely), the observed correlation between age and vintage may even be negative for high enough values of f. In short, our model allows us to recover $\frac{\kappa}{f}$ (the relative costs of introducing new technologies either from incumbent updating and from entry) in part from the correlation of firms' vintages and their ages, the dispersion in firm ages and the dispersion in technology vintages..

The same figure also plots the correlation between productivity and age, and between log sales and their distance to the frontier, for different values of f. Again, with higher entry costs, greater incumbent technology upgrading (especially by high z firms) implies a higher correlation between log sales and age (high z firms upgrade their technologies and thus

[23] Here, $h(k)$ is a special case of the Beta(α, β) distribution, with $\alpha = 1$; β governs the extent to which entrants enter with technology vintages that are close to the frontier. With $\beta = 1$, k is uniformly distributed along the unit interval; as $\beta \to \infty$, entrants' enter with frontier technologies with probability approaching 1.

[24] The value of entry $V(0, z)$ is homogeneous of degree one in κ and f. Since the moments we wish to match are orthogonal to the total mass of firms (which all that $V(0, z)$ pins down), we are free to normalize either κ or f. Furthermore, since our model will be identified off of dispersion in firms variable profits, η and σ will not be separately identified; see Equation 7.

Our choice of δ^A implies that firms exit for exogenous reasons once every 1000 years. We choose a small but positive value for δ^A so that nearly all exit in our simulations occurs because of technological obsolescence — the force we wish to highlight — but that even the highest z firms exit eventually. Our decomposition results, on the importance of net entry for industry technology upgrading, are invariant to increasing δ^A up to 0.002 or down to 0.0005.

[25] These parameter values correspond to those that minimize our SMM objective funciton; see Equation 13, below.

We outline our algorithm to construct these simulated moments in Appendix D.

survive longer) and a more negative correlation between firms' log sales and their distance to the frontier.

In the top right panel, we again vary f but plot the dispersion in firms' ages and their sales. With higher f, greater incumbent technology updating entails longer survival for certain firms, primarily high productivity firms. This implies greater dispersion in firms' ages, and — since more high-productivity firms participate in the market — greater dispersion in firm sales. In the bottom left panel of Figure 3, we again depict dispersion in firms' log sales and their ages, now varying the dispersion in entrants' productivity levels Increases in σ mechanically translate to increases in firms' log sales. With more dispersion in productivity,there is greater dispersion in the returns from technology updating, yielding an increase in the dispersion in firms' ages. Overall, the dispersions of age and sales each depend both f and σ, however with differing sensitivities.

Finally, and with the aim of communicating how T is identified, the bottom right panel of Figure 3 plots various moments as functions of T. Mechanically, as T increases, the standard deviation of firms' ages and their vintages increases. However, since increasing the period length effectively increases firms' discount rate, with lower T incumbents engage in more technology upgrading, leading to more longer-lived firms and thus to a more firm age distribution. In sum, holding other parameters fixed, higher T is associated with more dispersed firm vintages, and less dispersed firm ages.

We estimate f, T, β, and σ via a simulated method of moments procedure. Our seven moments are the standard deviations (i) of firms' log sales, (ii) of firms' age, (iii) and of firms' distance to the frontier; the correlations (iv) between firm log sales and age, (v) between firm log sales and distance to the frontier, and (vi) between firm age and distance to the frontier; and (vii) the average vintage of entrants (firms with age less than five years) relative to all firms. Using Θ to denote the five-dimensional vector of parameters we are trying to estimate, m^D to denote the seven-dimensional vector of moments, and $m(\Theta)$ to denote the simulated moments, our parameters minimize

$$\left(m(\Theta) - m^D\right) \cdot \left(\Sigma^D\right)^{-1} \cdot \left(m(\Theta) - m^D\right)' \quad . \tag{13}$$

Within this equation, Σ^D is the covariance matrix of our seven moments, which we compute by resampling from our dataset from 250 times.

Table 7 presents the results of our estimation. According to our model estimates, the length of time between the frontier technology and obsolete technologies are roughly $T = 15.10$ years. Second, the estimate of $\beta = 2.06$ implies that entrants have, on average, technologies that are roughly one-third $\left(\approx \frac{1}{2.06+1}\right)$ of the way between frontier and obso-

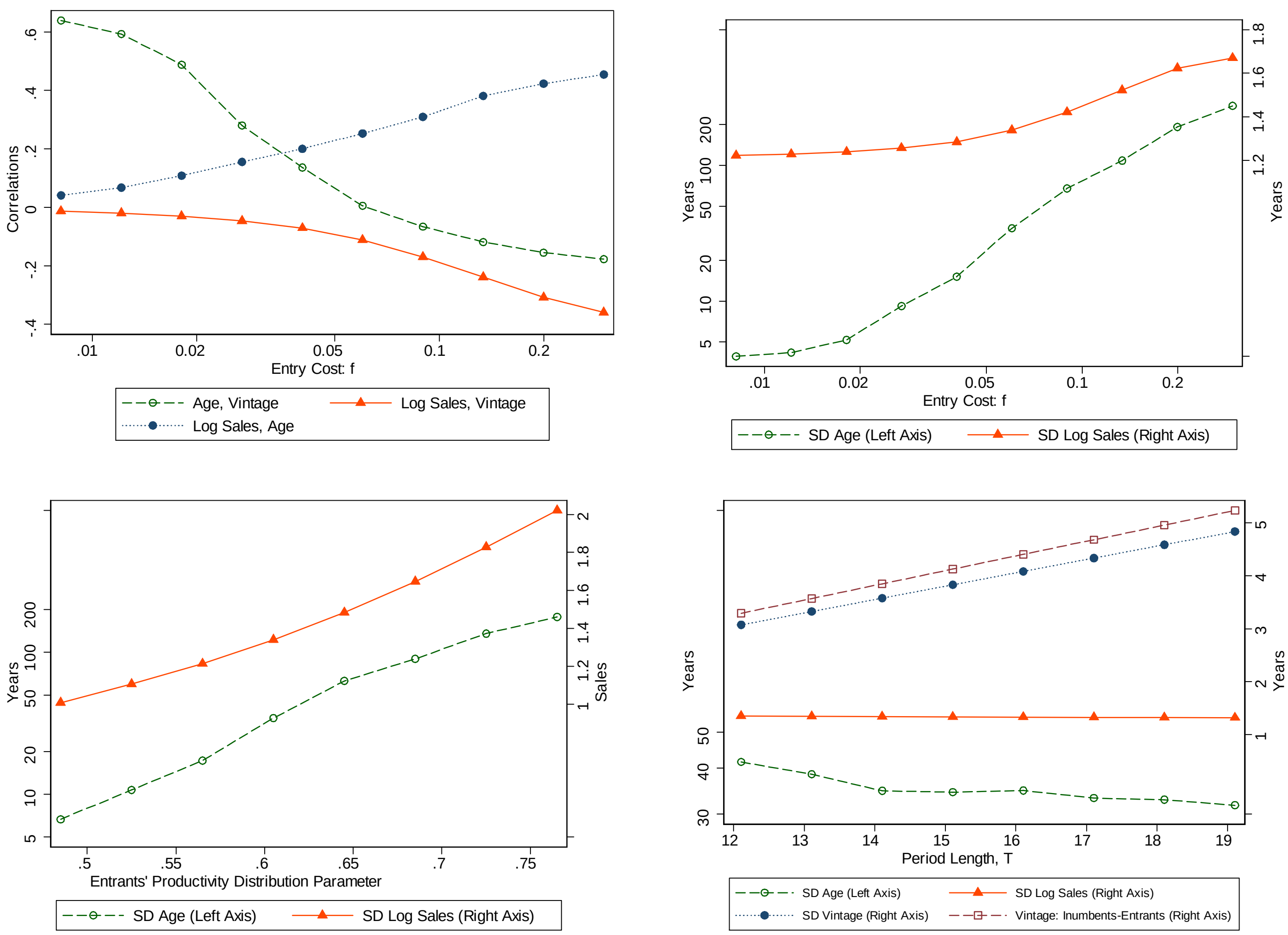

Figure 3: Comparative statics

Notes: Within these panels, age corresponds to $T \cdot a$, the period length multiplied by the number of periods that the firm has been in the industry; vintage refers to $Tcdotk$, the period length mulitplied by the firm's distance to the frontier; and, since sales are proportionate to variable profits, log sales is given by Equation 7. In all panels, we set $r^D = 0.02$, $\eta = 3$, and $\kappa = 1$.

	All		Manufacturing		Services	
Panel A: Moments	Model	Data	Model	Data	Model	Data
St. Dev. $(T \cdot a)$	34.44	35.45	31.16	31.03	38.41	39.08
St. Dev. $\log(c)$	1.34	1.66	1.36	1.76	1.34	1.46
St. Dev. $(T \cdot k)$	3.82	3.83	3.69	3.80	3.80	3.85
Corr$(\log(c), T \cdot a)$	0.25	0.33	0.24	0.27	0.26	0.41
Corr$(\log(c), T \cdot k)$	-0.11	-0.04	-0.10	-0.11	-0.11	0.07
Corr$(T \cdot a, T \cdot k)$	0.01	0.07	0.03	0.08	0.01	0.07
Incumbents $T \cdot k$ − Entrants $T \cdot k$	4.12	1.53	4.12	1.15	4.10	1.82
Panel B: Parameter Estimates						
f	0.060 (0.007)		0.050 (0.007)		0.062 (0.011)	
β	2.06 (0.02)		2.14 (0.04)		2.08 (0.02)	
σ	0.605 (0.016)		0.622 (0.018)		0.605 (0.018)	
T	15.10 (0.17)		14.61 (0.23)		14.97 (0.25)	
Panel C: Fraction of Upgrading Through Entry and Exit						
... when weighted by firm sales	0.558		0.573		0.546	
.... with no weights applied	0.914		0.926		0.912	

Table 7: Estimation results

Notes:In Panel A, we present the seven moments through which we estimate our model's parameters. In Panel B, we present our paramater estimates and corresponding asymptotic standard errors. In Panel C, we present the fraction of technology upgrading which occurs via incumbents (as opposed to entry and exit.) Computation of this fraction is described below. Manufacturing includes all firms which have SIC code between 2000 and 3999; services includes all other firms. Age $(T \cdot a)$ and distance to the frontier $(T \cdot k)$ are stated in terms of calendar years.

lete vintages. Overall, our model is able to fit the 7 moments reasonably well, though our estimated model understated the dispersion in firms' sales and the difference between incumbents' and entrants' vintages.

With the estimates of f, σ, β, and T in hand, we now decompose the sources of technology upgrading. In the left panel of Figure 4, we plot the exit rate as a function of z. In our stationary equilibrium, for each firm that exits (with a distance to the frontier equal to 1) a new firm with a technology dawn from the $h(k)$ distribution. With $\beta = 2.06$, the expected value of entrants' distance to the frontier equals 0.33. Incumbent firms with low z choose not to pay the technology upgrading cost, leading to low values of λ for these firms. As a result, low z firms exit approximately $1.5(\approx \frac{1}{1-0.33})$ times per model period (see the left portion of the line depicted with "+" signs.) High z firms tend to have higher rates of technology upgrading, and thus avoid obsolescence for longer. In the same plot, with hollow circles, we depict the rate of vintage upgrading that occurs through entry and exit.

Conversely, as the top right panel of Figure 4 illustrates, high z firms tend to update their vintages more frequently than low z firms. For firms with $z > 4.7$, vintage upgrading occurs at least once per model period (see the line depicted with "+" signs). Since technology upgrading involves both firms with k close to 1 and those with k substantially less than 1 upgrading to the frontier technology, we must integrate over the possible values of k to compute the rate at which new vintages replace old ones through incumbents' innovation decisions. The second line (depicted with hollow circles) within the figure's top right panel presents this.

Combining the results from the top two panels, the bottom left panel presents the fraction of technology upgrading that occurs via entry and exit as opposed to incumbents' upgrading. For firms with $z < 3.5$, vintage upgrading occurs primarily through entry and exit; for high productivity firms the opposite is true.

In the bottom right panel, we plot the productivity distribution, both for incumbents and for all firms. Since high productivity firms update their technologies more frequently, relative to the entrants' productivity distribution (dashed line), there are more surviving firms in the right tail. Integrating over the distribution of firms in our simulated economy, and weighting firms equally, we find that 91 percent of technology adoption occurs through the entry and exit margin. Incumbent firm innovation accounts for the remaining 9 percent. However, high z firms represent a greater fraction of consumers' sales. On a sales-weighted basis, 44 percent of firm innovation occurs through incumbents' vintage upgrading.

In the final columns of Table 7, we consider heterogeneity between the manufacturing and service sectors. In part driven by firms in the banking, education and health industries, service sector firms are on average older than in the manufacturing sector. At the same time, the dispersion in firms' distances to the frontier are similar between the manufacturing and service sectors. As a result., our model identifies a lower entry cost to manufacturing firms. In turn, we identify a larger role for the net entry margin in manufacturers' technology upgrading.

6 Conclusion

Drawing on newspaper vacancy postings from 1940 to 2000, this paper documents that 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

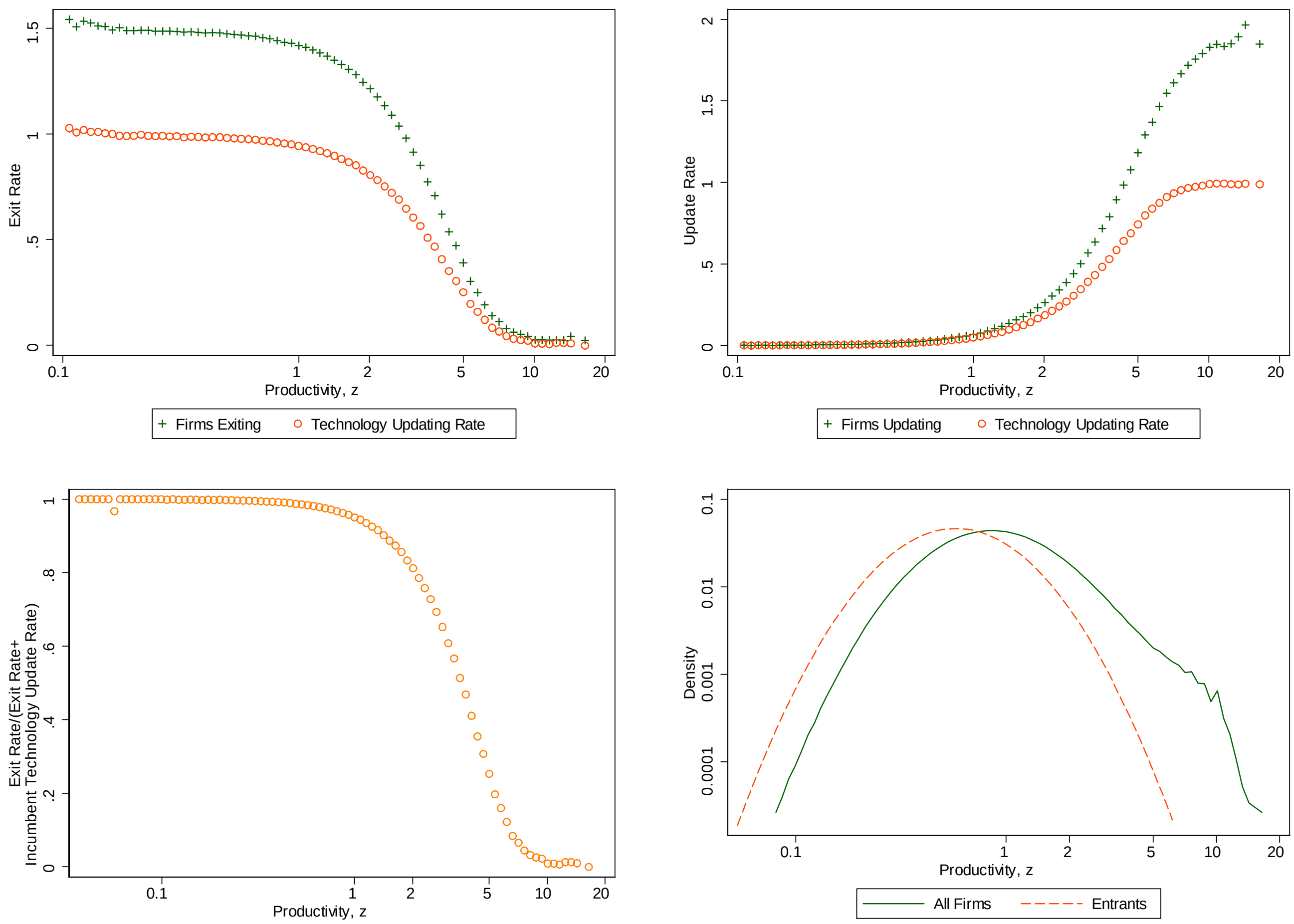

Figure 4: Sources of Vintage Upgrading

Notes: The top left panel gives the rate at which firms with a given value of z exit the industry ("+" signs) and the rate at which technology vintages are upgraded through entry and exit (hollow circles). The top right panel presents both the rate at which incumbent firms upgrade their vintages ("+" signs) and the rate at which incumbent firm technologies are upgraded (hollow circles.) The bottom left panel presents the fraction of technology upgrading that occurs via entry and exit (taken from hollow circles of the top left panel) versus incumbents' technology upgrading (taken from the hollow circles from the top right panel). The bottom right panel presents the productivity distribution, both the assumed log-normal distribution for entrants and the endogenously determined distribution among all firms. For these figures, we use the parameter estimates presented in the first column of Table 7.

for such workers ultimately perform poorly or disappear. In sum, since many employer-employee relationships are long-lived, vacancy postings not only lead to new hires, but also provide a window to researchers on firms' aspirations and capabilities over the next several years.

Motivated by these patterns, we develop an industry equilibrium model of technology upgrading. As time progresses, firms fall further and further behind the technological frontier, and, without successfully upgrading their technology, exit the industry. Exiting firms are replaced by entrants with relatively newer vintage technologies. We estimate our model using information on the distribution of firms' sales, ages, and job title vintages. Based on this estimation, we find that both channels of technology upgrading play an important role.

Our starting point in this paper has been to construct a single summary measure of firms' adoption of new technologies. But our approach, drawing on detailed information from the job ads that firms place, permits richer analyses, differentiating jobs according to their function. Certain groups of jobs are informative about firms' innovative activities in managerial and organizational domains; other groups of jobs are informative about firms' technological capabilities. Do firms' placement of newer vintage organizational and technological job ads occur at different points in their life cycles? Are hiring for newer work practices in organizational jobs and technological jobs complementary to one another? We leave an analysis of these questions to future work.

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A Additional Details on Processing the Job Ad Text

In this appendix, drawing on Atalay, Phongthiengtham, Sotelo, and Tannenbaum (2018, 2020), 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 following paragraph quotes 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. In addition, we search for mentions of 48 individual technologies which are mentioned at various points of the 1940.[26]

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," "assoc," "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.

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.

[26] 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.

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.

SENIOR 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 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 5: 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 (2020) .

An Example

Figures 5 and 6 illustrate the performance of our text-processing algorithm. Figure 5 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 6 presents the results of our text-processing procedure. The Atalay, Phongthiengtham, Sotelo, and Tannenbaum (2020) 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. New, relative to Atalay, Phongthiengtham, Sotelo, and Tannenbaum (2020), 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 identifies useful information related yo 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.*[27]

B Representativeness of the Main Sample

Of the ads that were originally posted in the *Boston Globe, New York Times,* and *Wall Street Journal* we have only been able to identify who was posting the ad in a fraction of cases. Further, many of these ads were posted not by the firm that would eventually hire the worker but instead by a placement agency — who matches employers and job seekers — or only contain a phone number or address to which an application could be sent. Our main analysis focuses only on the set of ads for which we can identify the employing firm. How representative is this subset of ads among the broader sample? And has this representativeness changed over time?[28]

[27] 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.

[28] In Atalay, Phongthiengtham, Sotelo, and Tannenbaum (2020), we assess the representativeness of our sample of ads from our three major metropolitan newspapers in measuring the overall workforce. First, compared to other channels through which job seekers find work — e.g., going directly to the plant, referrals from friends or family — jobs filled through newspaper advertisements tend to be relatively more high skilled, centered on managerial, financial, and administrative occupations. These differences are constant over our sample period. Second, using a sample of online job ads we measure differences in the characteristics of job

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 6: Processed text from the April 10, 1960 *New York Times*.

Notes: We identify six 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. The six-digit code in square brackets refers to the SOC code which we have identified: 151143 is the code for Compte Network Archicts; 132011 is the code for Accountants and Auditors; 172141 is 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. In a later stage, we drop the "Senior" job ad, since the title we have identified does not correspond to a recognizable job.

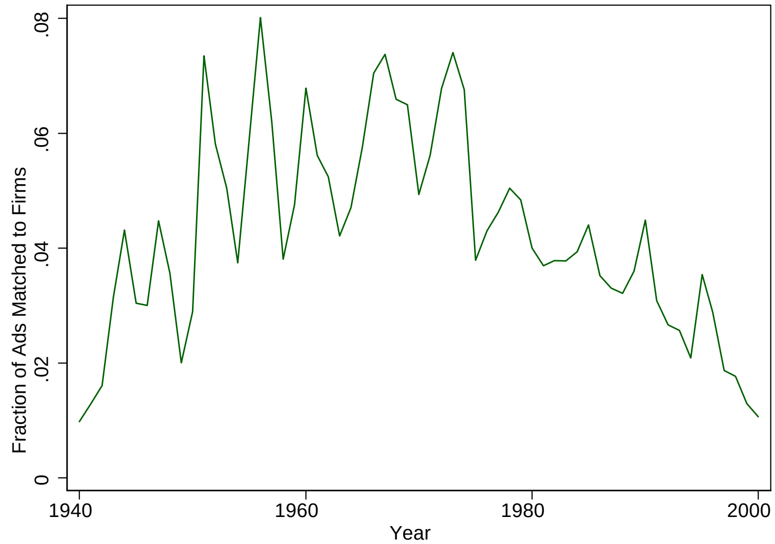

Figure 7: Fraction of Ads Corresponding to an Employer.
The sample includes the 5.21 million ads corresponding to job titles that appear at least 20 times.

To address these questions, we first plot in Figure 7 the fraction of ads for which we can identify the employing firm. Overall, there is an increase in the fraction of ads up to the midpoint of our sample, from 2.7 percent in the 1940s to 5.9 percent in the 1960s, then a decline to 2.5 percent in the 1990s.

We next compare job ad characteristics to selection into our sample. Our regressions correspond to the following equation:

$$x_{at} = \beta_t + \beta_1 \cdot \mathbf{1}\{\text{agency, street address, or phone number identified}\} \\ + \beta_2 \cdot \mathbf{1}\{\text{employer name identified}\} + \epsilon_{at} \quad . \tag{14}$$

Within Equation 14, x_{at} denotes any characteristic of ad a posted in year t and β_t denotes year fixed effects. Our coefficients of interest, β_1 and β_2, capture differences between ads for which we could not identify the posting party (the omitted base group) and ads for which we identify a phone number, street address, or placement agency (β_1) and ads for which we can identify the employer (β_2). Overall, we find that ads with firms in our sample tend to mention graduate degrees less frequently and technologies more frequently (columns 2, 3, 8, 9, 14, and

ads posted in Boston and New York compared to those in the rest of the country. We find that job ads in Boston and New York tend to mention words associated with information and communication technologies more frequently, nonroutine tasks more frequently, and routine tasks less frequency. These differences occur both across occupations — e.g., there are relatively more engineers and investment bankers in Boston and New York — and within occupations — e.g., there are more mentions of nonroutine interactive tasks for any occupation — with a majority of these differences occuring across occupations.

15 of Table 8) To help gauge the economic significance of these estimates, in the final row of each panel, we list within-year standard deviation of x_{ft}: the root mean squared error of a regression of the job characteristic on year fixed effects. Ads with an employer observed have 0.09 standard deviations ($\approx -0.670/7.551$) fewer mentions of a graduate degree. Depending on the job title vintage measure, ads in our benchmark sample have somewhat newer (in the case of $v_{j(a)}^{0.01}$) or older (in the case of $v_{j(a)}^{0.99}$) job titles. In panels B and C, we compare the estimated relationships across the two halves of our sample. We find that ads with an identified posting firm tended have older job titles (using the $v_{j(a)}^{0.50}$ measure) in the first half of the sample but newer job titles in the second half. We also find that ads with a posting firm tend to mention undergraduate degrees somewhat less frequently in the first half of the sample, somewhat more frequently in the second half. Besides these two differences, there were no notable differences in the estimate of β_2 across the two halves of the sample.

C Additional Calculations Related to Section 3 and 4

C.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.

C.2 Sensitivity Analysis Related to Section 4

Within Section 4 regressions our analysis weighted each observation according to the number of ads corresponding to each firm-year observation. In this appendix, we present the analogues of Tables 2- 6, with observations now weighted equally. Overall, we find that the main patterns presented in Section 4 are invariant, qualitatively, to weighting observations by the number of ads or not, though some of the magnitudes are smaller in unweighted specifications.

Panel A: All Years	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Undergrad. Degree	Graduate Degree	Technology	$v_{j(a)}^{0.01}$	$v_{j(a)}^{0.50}$	$v_{j(a)}^{0.99}$
Agency, Phone	-0.163	-0.328	0.036	0.251	-0.113	-0.423
.Number or Address	(0.006)	(0.012)	(0.010)	(0.012)	(0.016)	(0.011)
Firm in our sample	0.035	-0.670	0.396	0.826	-0.036	-1.570
	(0.008)	(0.015)	(0.013)	(0.015)	(0.021)	(0.014)
RMSE(Year Only)	4.125	7.551	6.174	7.339	10.218	7.050
Panel B: 1940-1969	(7)	(8)	(9)	(10)	(11)	(12)
Dependent Variable	Undergrad. Degree	Graduate Degree	Technology	$v_{j(a)}^{0.01}$	$v_{j(a)}^{0.50}$	$v_{j(a)}^{0.99}$
Agency, Phone	-0.080	-0.183	-0.028	0.109	0.099	-0.368
.Number or Address	(0.008)	(0.015)	(0.006)	(0.009)	(0.020)	(0.019)
Firm in our sample	-0.053	-0.820	0.084	0.591	-0.245	-2.163
	(0.010)	(0.018)	(0.007)	(0.011)	(0.024)	(0.022)
RMSE(Year Only)	3.711	7.062	2.811	4.279	9.250	8.532
Panel C: 1970-2000	(13)	(14)	(15)	(16)	(17)	(18)
Dependent Variable	Undergrad. Degree	Graduate Degree	Technology	$v_{j(a)}^{0.01}$	$v_{j(a)}^{0.50}$	$v_{j(a)}^{0.99}$
Agency, Phone	-0.254	-0.486	0.109	0.410	-0.345	-0.477
.Number or Address	(0.011)	(0.019)	(0.020)	(0.023)	(0.026)	(0.010)
Firm in our sample	0.180	-0.425	0.895	1.200	0.306	-0.615
	(0.015)	(0.027)	(0.029)	(0.033)	(0.038)	(0.014)
RMSE(Year Only)	4.616	8.153	8.837	10.046	11.373	4.375

Table 8: Estimation of Equation 14.
The sample includes the 5.21 million ads corresponding to job titles that appear at least 20 times. Each row presents the coefficients and standard errors of β_1 and β_2. In addition, we give the root mean squared error of residuals from a regression of the dependent variable on year fixed effects.

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 9: 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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Variable		——	$\log(y_{it})$	——		——	$\log(lp_{it})$	——
Avg. Year of Emergence$_{it}$			-0.013				-0.0014	
			(0.005)				(0.0009)	
Avg. Median Year$_{it}$	-0.006	-0.004		-0.006	-0.0028	-0.0016		–0.0015
	(0.004)	(0.004)		(0.004)	(0.0008)	(0.0007)		(0.0008)
Avg. Year of Disappearance$_{it}$			-0.006				0.0023	
			(0.007)				(0.0015)	
Other Controls	None	Industry F.E.		Industry F.E. SOC Shares	None	Industry F.E.		Industry F.E. SOC Shares
R^2	0.154	0.179	0.187	0.186	0.844	0.876	0.877	0.877
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Dep. Variable		——	$\log(\text{R\&D}_{it}/y_{it})$	——		——	$\log(\text{R\&D}_{it}/y_{it})$	——
Avg. Year of Emergence$_{it}$			0.015				0.007	
			(0.004)				(0.015)	
Avg. Median Year$_{it}$	0.013	0.012		0.010	0.060	0.044		0.025
	(0.003)	(0.003)		(0.003)	(0.014)	(0.012)		(0.013)
Avg. Year of Disappearance$_{it}$			0.011				0.016	
			(0.007)				(0.023)	
Other Controls	None	Industry F.E.		Industry F.E. SOC Shares	None	Industry F.E.		Industry F.E. SOC Shares
R^2	0.137	0.245	0.262	0.255	0.238	0.441	0.452	0.452

Table 10: Relationship between job title vintage, sales, productivity, and R&D intensity.

Notes: See the notes for Table 2. Compared to that table, observations are equally weighted.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Variable	———	——— log $(y_{i,t+5}/y_{it})$		———	——	—— log $(y_{i,t+10}/y_{it})$		——
Avg. Year of Emergence$_{it}$			0.003 (0.001)				0.004 (0.002)	
Avg. Median Year$_{it}$	0.005 (0.001)	0.005 (0.001)		0.004 (0.001)	0.006 (0.002)	0.005 (0.002)		0.003 (0.002)
Avg. Year of Disappearance$_{it}$			0.001 (0.002)				0.002 (0.003)	
Other Controls	None	Industry F.E.		Industry F.E. SOC Shares	None	Industry F.E.		Industry F.E. SOC Shares
R^2	0.160	0.180	0.184	0.185	0.188	0.210	0.214	0.214

	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Dep. Variable	———	——— log $(y_{i,t+10}/y_{it})$		——	———	——— log $(lp_{i,t+10}/lp_{it})$		——
Avg. Year of Emergence$_{it}$			0.012 (0.004)				0.008 (0.004)	
Avg. Median Year$_{it}$	0.015 (0.003)	0.014 (0.003)		0.012 (0.004)	0.008 (0.003)	0.007 (0.003)		0.007 (0.003)
Avg. Year of Disappearance$_{it}$			0.009 (0.006)				0.003 (0.006)	
Other Controls	None	Industry F.E.		Industry F.E. SOC Shares	None	Industry F.E.		Industry F.E. SOC Shares
R^2	0.039	0.045	0.047	0.047	0.042	0.049	0.050	0.050

Table 11: Relationship between job title vintage, sales growth, and labor productivity growth.
Notes: See the notes for Table 3. Compared to that table, observations are equally weighted.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	Publicly Traded			Publicly Traded Within 10 Years?		
Avg. Year of Emergence$_{it}$		0.0004 (0.0008)			0.0021 (0.0007)	
Avg. Median Year$_{it}$	0.0025 (0.0005)		0.0014 (0.0006)	0.0024 (0.0005)		0.0023 (0.0006)
Avg. Year of Disappearance$_{it}$		0.0022 (0.0007)			0.0031 (0.0007)	
Other Controls	Industry F.E		Industry F.E. SOC Shares	Industry F.E.		Industry F.E. SOC Shares
R^2	0.157	0.165	0.165	0.064	0.065	0.064

Table 12: Relationship between job title vintage and firms' publicly traded status.
Notes: See the notes for Table 4. Compared to that table, observations are equally weighted.

C.3 Narratives

With the goal of making our Section 4 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 8 plots the relationship between firms' sales growth and their average vintages (according to the Avg. Median Year variable). To facilitate comparison across points in time, for each firm-year ($i - t$) 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 3, Figure 8 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 per-

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Variable	——	$\log\left(\text{patents}_{i,t}+1\right)$		——	——	$\log\left(\text{citations}_{i,t}+1\right)$		—
Avg. Year of Emergence$_{it}$			-0.004				-0.005	
			(0.002)				(0.003)	
Avg. Median Year$_{it}$	0.003	0.005		0.001	0.005	0.008		0.003
	(0.002)	(0.002)		(0.002)	(0.002)	(0.002)		(0.002)
Avg. Year of Disappearance$_{it}$			0.003				0.005	
			(0.002)				(0.002)	
Other Controls	None	Industry F.E.		Industry F.E. SOC Shares	None	Industry F.E.		Industry F.E. SOC Shares
R^2	0.140	0.241	0.253	0.253	0.163	0.269	0.283	0.282
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Dep. Variable	——	$\log\left(\text{patents}_{i,t}+1\right)$		——	——	$\log\left(\text{citations}_{i,t}+1\right)$		—
Avg. Year of Emergence$_{it}$			-0.004				-0.005	
			(0.004)				(0.005)	
Avg. Median Year$_{it}$	0.002	0.001		-0.003	0.004	0.002		-0.004
	(0.003)	(0.003)		(0.003)	(0.004)	(0.004)		(0.015)
Avg. Year of Disappearance$_{it}$			-0.005				-0.005	
			(0.005)				(0.008)	
$\log\left(\text{R\&D}_{it}/y_{it}\right)$	0.123	0.088	0.086	0.086	0.177	0.127	0.124	0.124
	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Other Controls	None	Industry F.E.		Industry F.E. SOC Shares	None	Industry F.E.		Industry F.E. SOC Shares
R^2	0.490	0.530	0.535	0.535	0.501	0.539	0.544	0.544

Table 13: Relationship between job vintage and patenting activity.
Notes: See the notes for Table 5. Compared to that table, observations are equally weighted.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	Entry Year			Exit/Acquisition Year		
Avg. Year of Emergence$_{it}$		0.220 (0.065)			0.175 (0.093)	
Avg. Median Year$_{it}$	0.202 (0.046)		0.212 (0.050)	0.092 (0.062)		0.086 (0.067)
Avg. Year of Disappearance$_{it}$		0.140 (0.067)			-0.051 (0.098)	
Other Controls	Industry F.E.		Industry F.E. SOC Shares	Industry F.E.		Industry F.E. SOC Shares
R^2	0.204	0.206	0.206	0.031	0.033	0.033

	(7)	(8)	(9)	(10)	(11)	(12)
Dep. Variable	Entry Year to Compustat			Exit Year from Compustat		
Avg. Year of Emergence$_{it}$		0.120 (0.036)			0.142 (0.055)	
Avg. Median Year$_{it}$	0.057 (0.030)		0.065 (0.032)	0.185 (0.044)		0.147 (0.047)
Avg. Year of Disappearance$_{it}$		0.100 (0.065)			0.213 (0.084)	
Other Controls	Industry F.E.		Industry F.E. SOC Shares	Industry F.E.		Industry F.E. SOC Shares
R^2	0.072	0.074	0.073	0.016	0.019	0.019

Table 14: Relationship between job vintage, entry year, and exit year.
Notes: See the notes for Table 6. Compared to that table, observations are equally weighted.

formance, storage, packaging, and price." (Ceruzzi, 2003, p. 130)[29] To develop these new products, DEC hired workers in a number of emerging jobs, primarily but not limited to technological occupations. In the late 1960s, DEC posted multiple ads for *Application Programmer*, *Field Service Engineer*, and *Systems Programmer* jobs. All three of these job titles emerged after 1955. 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_{it} variable) was over 5 years newer than other ads posted by publicly traded firms. And, consistent with our earlier statistical analysis from Section 4, 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 billion in 1980. (All dollar figures are stated relative to the 2017 CPI.) Into the late 1970s, DEC adopted newer and newer vintage work practices: It posted multiple ads for *Application Software Manager* and *Device Driver Development* jobs, both which emerged only after 1975.

Our second example comes from slightly later in our sample — Wang Laboratories. Initially a manufacturer of electronic calculators, Wang Laboratories successfully transitioned into designing and manufacturing word processing equipment in the 1970s.[30] 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 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.

At the other end of the spectrum from DEC and Wang Labs are firms like American

[29] 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)

[30] 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)

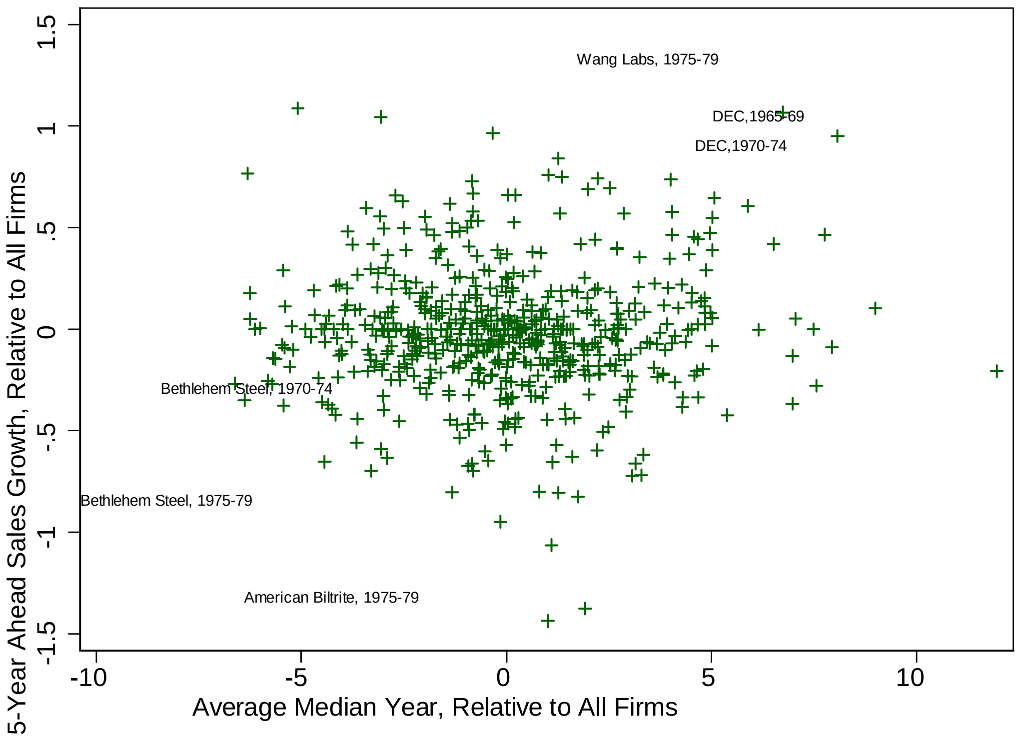

Figure 8: Relationship between firm vintages and sales growth.

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, for visual clairty, we omit firm-five-year-period pairs for which the firm posted fewer 25 ads within the given five-year period. We have also omitted from this plot an additional observation 1970-74 Cowles Company, which had average sales growth 297 log points below average. 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. Bethlehem Steel posted 50 ads between 1970 and 1974 and 37 ads between 1975 and 1979. DEC posted 210 ads between 1970 and 1974 and 363 ads between 1975 and 1979. 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 0.16.

Biltrite and Bethlehem Steel. 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.[31] 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. Bethlehem Steel, as well, had a period of exceptionally slow growth in the 1970s in conjunction with a preponderance of advertisements in disappearing job titles (including *Coppersmiths*, *Linotype Operators*, and *Stenographers*.)

To emphasize, we do not wish to imply that the management of American Biltrite or Bethlehem Steel 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 or Bethlehem Steel, 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.

D Algorithm to Construct Simulated Moments

In this appendix, we outline our algorithm to construct our simulated moments. Take as given a set of parameter values $\Theta \equiv \{f, T, \beta, \sigma\}$. Also, let $\lambda\left(z, k; \Theta\right)$ refer to firms' decision rules. We split each model period into increments of $\chi = \frac{1}{200}$. We simulate 5 million model periods. For each of the $5 \cdot 10^6 \cdot \chi$ =1 billion model period increments, we do the following:

- Draw $\tilde{\lambda}$ and $\tilde{\delta}$ from a uniform distribution.[32] If $\tilde{\delta} < \chi \cdot \frac{\delta^A}{T}$, the firm "exits".
  - For a firm that exits, it is replaced by a new firm with age $a = 0$, distance to the frontier k drawn from the Beta$(1, \beta)$ distribution, and TFP z drawn from a log-normal$\left(-\frac{1}{2}\sigma^2, \sigma^2\right)$ distribution.

[31] 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)

[32] In our SMM estimation, the random variables that we draw are retained, so that the same realizations are used for each combination of Θ.

- If $\tilde{\delta} > \chi \cdot \frac{\delta^A}{T}$ and $\tilde{\lambda} < \lambda(z, k; \Theta) \cdot \chi$, the firm updates its vintage:
  - For a firm that updates its vintage, the age a increases by χ, and the distance to the frontier k equals 0.
- If $\tilde{\delta} > \chi \cdot \frac{\delta^A}{T}$ and $\tilde{\lambda} > \lambda(z, k; \Theta) \cdot \chi$:
  - If $k < 1$, the age and distance to the frontier each increase by χ.
  - If $k = 1$, the firm exits. It is replaced by a new firm with age $a = 0$, distance to the frontier k drawn from the Beta$(1, \beta)$ distribution, and TFP z drawn from a log-normal$\left(-\frac{1}{2}\sigma^2, \sigma^2\right)$ distribution.

The result of this procedure is a sample of 1 billion observations, with each observation containing information on age (a), TFP (z), and distance to the frontier (k). Note that log sales is proportional to log TFP.