Mismatch in Online Job Search

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Abstract

Public debate has recently focused on whether or not people have the skills for the jobs in today's economy. Past research quantifying this mismatch in the labor has focused on piecing together data from different sources to build a complete picture of the labor market. In this paper we instead use data from a major online job site with rich information on both the job seekers and the vacancies. In this preliminary version we focus on the aggregate measure from January of 2014 through July of 2018 including both employed and unemployed job seekers. Our key findings are that mismatch is substantial, hovering at about 33%, but that it has not worsened as the labor market has tightened. Furthermore, over the past four years job opportunities have shifted substantially, but job seekers appear to be largely keeping up. We also detail a number of next steps that are feasible with our unique dataset, including a focus on using our measure of mismatch to relate to macroeconomic conditions.

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Introduction

Public debate has recently centered on whether or not there are structural problems in the labor market in terms of a mismatch between the background, skills, or interests of job seekers as compared to the needs perceived by employers. The "skills gap" or "talent shortage" conversation often relies on anecdotes because it can be hard to collect data at a sufficiently detailed level to appropriately quantify mismatch. Previous research has provided measures based on connecting data from a variety of different sources with varying levels of detail. Online labor market data provides the potential for new insights based a single source of rich data on both vacancies and job seekers.

The mismatch index is designed to measure the level of mismatch, or dissimilarity, in the economy. It compares the number of job seekers in a job category to the number of vacancies in the same category. Mismatch can arise because there are too few or too many job seekers in a particular category relative to the number of job opportunities. Importantly, our measure of mismatch is relative to the overall availability of job seekers and vacancies and we are focused here on the mismatch across categories rather than movements in the aggregate job seeker to vacancy ratio.

Our analysis is closely related to Şahin et al. (2011 and 2014) and Lazear and Spletzer (2012a, 2012b) who also quantified the level of mismatch in the economy. They use publicly available data from BLS (JOLTS and CPS) and measure mismatch based on industry categories. They also use vacancy data from the Conference Board's Help Wanted Online Index to construct mismatch measures for a set of occupation categories.[2]

Şahin et al. (2014) focus on measuring "mismatch unemployment", i.e. the share of unemployment due to sectoral mismatch. For their occupation-level analysis they report results using 22 or the 23 major (two-digit) SOC groups and 36 of 96 minor (three-digit) SOC groups. In the working paper version, Şahin et al. (2011) use the same mismatch formula we use here for a benchmark measure with no heterogeneity across markets. They consider all 17 industries

[2] There has also been substantial research on mismatch outside the US and particularly in the UK. Turrell et al. use data from Reed, an online recruiter in the UK, to estimate mismatch by occupation and geography in the UK. They find that it is regional mismatch rather than occupational mismatch that affects UK productivity. Patterson et al. (2016) and Smith (2012) used data from the UK government employment agency JobCentre Plus to construct estimates of mismatch with Patterson et al. finding that occupational mismatch is an important contributor to weak productivity growth in the UK and Smith finding that occupational mismatch has had a substantial impact on UK unemployment rates.

where JOLTS vacancy data are available.[3] They conclude that mismatch explains up to one third of the increase in the unemployment rate during the Great Recession.

Lazear and Spletzer (2012a, 2012b) used a measure of mismatch as part of a broader set of indicators on the recent performance of the US labor market. In terms of mismatch they focused on their finding that mismatch rose in the recession and then declined afterwards suggesting a cyclical rather than structural pattern.

Our goal is to create a set of mismatch indexes that we will update over time. Similar to Lazear and Spletzer, we are particularly interested in what the patterns in our mismatch measures over time tell us about how different types of mismatch are related to changes in economic conditions. With our unique dataset we can focus on a range of different levels of disaggregation to create different measures of mismatch. For example, we include both employed and unemployed job seekers in our benchmark series. Including employed job seekers which has been challenging in previous analyses due to limited data availability on people searching on the job.[4]

In the following sections we describe our data, provide an analysis similar to Şahin et al (2011) and Lazear and Spletzer (2012a & b) to produce a measure of industry mismatch using publicly available data, then estimate a preliminary measure of overall online labor market mismatch. We find that mismatch has not increased as the labor market has tightened and also show that the distribution of jobs has changed substantially over this time period. We then discuss robustness checks and conclude with a discussion of next steps.

Data

Currently all our analysis is focused on the US. Our main data source is online job postings and job seekers from Indeed, the largest job site in the world based on unique visitors according to ComScore, an independent analytics firm.[5] We also use data from the Current Population

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[3] The 17 industries used by Şahin et al. are: arts, construction, mining, accommodations, retail, professional business services, real estate, wholesale, other, transportation and utilities, manufacturing - nondurables, education, health, government, manufacturing - durables, finance, and information. The 12 industries we use in our analysis are: construction, durable goods manufacturing, nondurable goods manufacturing, wholesale and retail trade, transportation and utilities, information, financial activities, professional and business services, education and health services, leisure and hospitality, other services, and government. Lazear and Spletzer use 12 industries but differ from ours by including mining but grouping together durable and nondurable goods manufacturing. We exclude mining due to different definitions between JOLTS and CPS. Results are little changed between the different choices of Lazear and Spletzer, Şahin et al. or our analysis.

[4] Şahin et al. (2014) did provide an estimate of their measure including on-the-job search. They used the American Time Use Survey to identify employed job seekers. This survey likely underestimates the number of employed job seekers as discussed in Faberman et al. (2017).

[5] Over 200 million unique visitors per month globally and, per Google Analytics, 62.0 million per month in the US as of January 2018. Furthermore, in August 2017, comScore estimated that 70% of US online job seekers search for jobs on Indeed (per month)

Survey (CPS) and the Job Openings and Labor Turnover Survey (JOLTS).[6] We focus on seasonally unadjusted data from all sources. Our measure of mismatch will be in shares of totals which should net out any national seasonal patterns and will leave only job category seasonal patterns which we are interested in examining.

Our measure of job openings will either be from JOLTS by industry, where we focus on the 12 industries where we can match with data available from the Bureau of Labor Statistics on the industry of the unemployed, or from job postings aggregated by Indeed from across the internet.[7]

It is important to note that we are not restricted to advertisers on Indeed. Instead they collect job postings anywhere on the internet and de-duplicate them as part of their business.

Our measure of job seekers will either be the unemployed from the CPS or active job seekers on Indeed. In our analysis we are focused on the job seekers who have accounts and have uploaded resumes to provide further detailed background information. Indeed has over 50 million resumes from the US as of July of 2018. We are focusing on the subset that were active accounts during our sample from 2014 through July of 2018, where active is defined as having updating their resume in that month.[8] We aggregate to the monthly frequency, but we could look at daily or even intra-day based on the Indeed data. Higher frequency is interesting when looking at the job seeker data (there are interesting daily and weekly patterns in the job search data), but less so for job posting data.

Job seekers are not just the unemployed.[9] In fact, it appears that the majority of job seekers on Indeed are employed based on reported employment status by account holders as well as reported in internal surveys. This is consistent with the finding by Faberman et al. (2017) that employed job seeking is "pervasive." We identify labor market status in the Indeed data based

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[6] The job openings data are from the September 11, 2018, release of JOLTS. The unemployed by industry data are from the CPS. The data are not seasonally adjusted, and using the 12 industries available from both CPS and JOLTS: construction, durable goods manufacturing, nondurable goods manufacturing, wholesale and retail trade, transportation and utilities, information, financial activities, professional and business services, education and health services, leisure and hospitality, other services, and government. Note that we exclude mining due to different definitions between JOLTS and CPS (although including it does not give noticeably different results).

[7] Şahin et al. (2011, 2014) and Lazear and Spletzer (2012a and b) also each produce measures of *occupational* mismatch using Help Wanted Online Index (HWOL) data as their measure of vacancies for a subset of standard occupation categories (since only industry groupings are available from JOLTS). The HWOL data by occupation is not publicly available and thus we focus on the industry mismatch as our comparison. Canon et al (2013) provide a review of mismatch indexes using HWOL job vacancy data.

[8] Indeed only saves the latest version of resumes, so we only count each resume one time based on latest update date, since the last job title from the resume is key to our analysis. We recognize this might cause a bias in the analysis if there is a systematic pattern in who updates resumes frequently and/or who was a job seeker on Indeed early in our sample and again later in our sample. We address this further in the robustness checks section.

[9] We're only looking at active job seekers, so they are either employed or unemployed, there is no "out of the labor force" group in our analysis.

on information reported by the user. Users opt-in to being counted as employed by checking a box indicating that they are currently employed at one of the positions listed on their resume. There is likely measurement error in this as some employed workers may not select the box and others may try to hide that they are unemployed by selecting the box or by not updating that information if they leave their employer but continue searching for a job on Indeed. We're also only looking at the "experienced unemployed" because we are only using resumes that have previous employment recorded. This is consistent with the BLS data where an industry is only available for people who were previously employed.

In the online labor market data we have much finer job type groupings than what is available in the data used in previous research: for our benchmark measure we include 6065 normalized title pairs per month in our analysis as compared to the 9 to 36 categories used by Lazear and Spletzer and Şahin (2012b) et al. (2014). For example, "registered nurse" is a normalized title that contains: Registered Nurse, RN, RN Staff Nurse, Registered Nurse (RN), Registered Nurse - RN, Registered Nurse Traveler, etc. "Economist" is a normalized title that contains: economist, health economist, principal economist, chief economist, associate economist, lead economist, and so on. We also estimated a version excluding low observation categories with functionally no impact on the estimates.

For robustness we also use an alternative measure of job seekers based on clicks on job postings. A job seeker can only click on a posting if one is available and the click many not indicate the job seeker is qualified, only interested in the role.

Methodology

The mismatch measure we're using is the Duncan and Duncan (1955) dissimilarity index. With this measure we're assuming that only the job seekers can change occupation whereas job vacancies are fixed in their category.[10] The Duncan and Duncan measure is:

$$\frac{1}{2}\sum_{i}\left|\frac{S_i}{S} - \frac{V_i}{V}\right|, \tag{1}$$

where S_i is the job seekers in category i, S is the total number of job seekers, V_i is the number of vacancies in category i, V is the total number of vacancies.

This is the same measure used by Lazear and Spletzer (2012a and 2012b) and Sahin et al. (2011, before incorporating a matching function). This index can be interpreted as the proportion of job seekers who would need to be moved to make the job seeker to posting ratio

[10] The Duncan and Duncan measure has come under criticism when applied to occupational gender segregation (Watts 1992, 1994, 1998). An alternative measure, the IP index of Karmel and MacLachlan (1988) is the preferred measure in that literature. In the gender segregation case, however, both men and women could change occupations, whereas in our analysis we assume only the job seeker can change occupations.

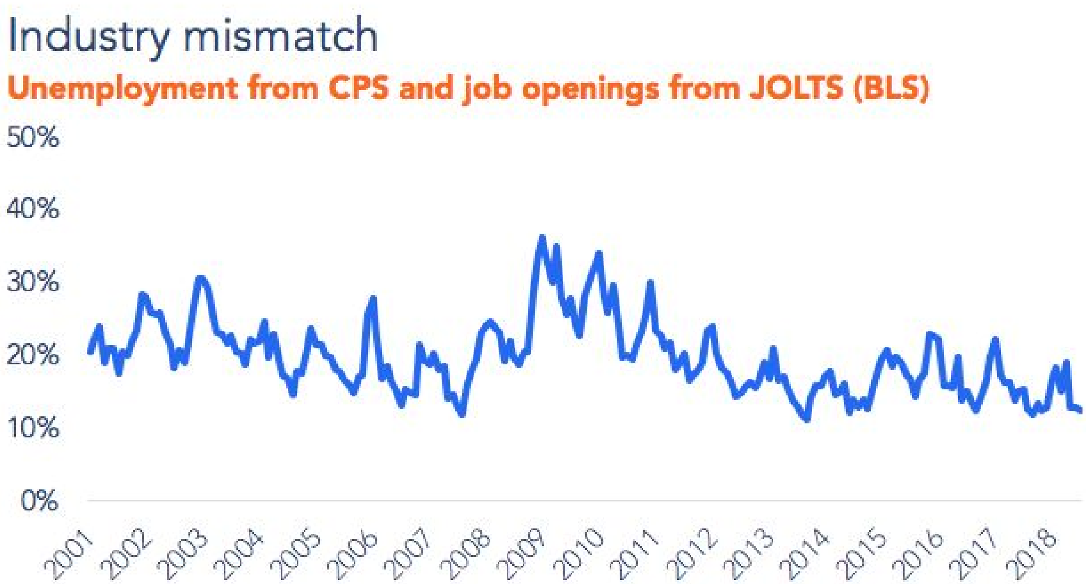
the same for all job categories, where a job category in our analysis will either be industry or normalized job title. Other measures of mismatch, notably Şahin et al. (2014), are reported as a fraction of hires lost per period due to job seeker misallocation. Thus our index will likely be much higher in magnitude as a share of job seekers as compared to a share of monthly hires.

Preliminary Results

We first produce an updated estimate of mismatch based on 12 industry categories that are available for vacancies from JOLTS and for the unemployed from the CPS data reported by the Bureau of Labor Statistics.[11] We estimate this industrial mismatch for the full sample where JOLTS vacancy data are currently available: December 2000 through July 2018.

Our estimates are reported in Figure 1. Similar to what was noted by Lazear and Spletzer (2012a and 2012b), we find that industry mismatch rose during the recession from the end of 2007 through mid=2009 and fell during the recovery. Interestingly it has remained fairly flat since 2014.

Figure 1: US labor market mismatch based on publicly available data

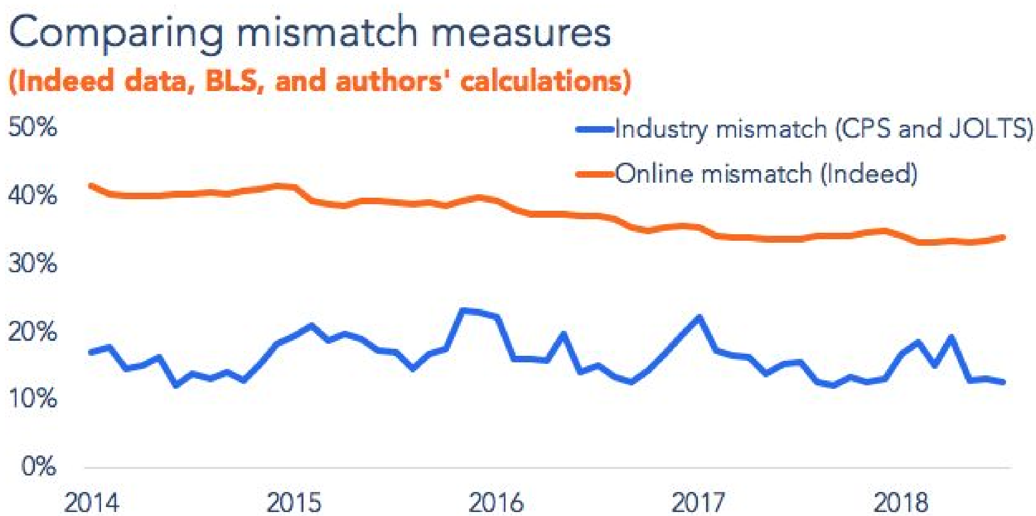


[11] The 12 industries available from both CPS and JOLTS are: construction, durable goods manufacturing, nondurable goods manufacturing, wholesale and retail trade, transportation and utilities, information, financial activities, professional and business services, education and health services, leisure and hospitality, other services, and government. Lazear and Spletzer use 12 industries by grouping together durable and nondurable goods manufacturing and including mining. Şahin et al. use CPS microdata to include all 17 industries available in JOLTS. Results are little changed between the different choices of Lazear and Spletzer, Şahin et al. or our analysis. The largest difference is due to our choice of using seasonally unadjusted data, but given that our mismatch measure is reported in shares, all national seasonal patterns are netted out.

For our measure of mismatch based on online job search we start in January of 2014 and go through July of 2018. One of the benefits of using the online data is more timely arrival which means we could already produce mismatch through August of 2018, but for this analysis we'll report the sample comparable to what is currently available in JOLTS, where the July 2018 data were only released on September 11th.

Figure 2 presents our preliminary online labor market mismatch estimate along with the data from Figure 1 for this time frame. Our measure is higher in level, as would be expected given that we're going from 13 categories to over 6000. In terms of time pattern, however, they're broadly similar, although our measure is substantially smoother.

Figure 2: Online Mismatch and Industry Mismatch



Lazear and Spletzer find much more mismatch by occupation than by industry, which is consistent with what we find for our online labor market mismatch at the normalized job title level. Job titles are much more similar to occupation than to industry. We would also expect that there would be more mismatch at lower levels of aggregation.[12]

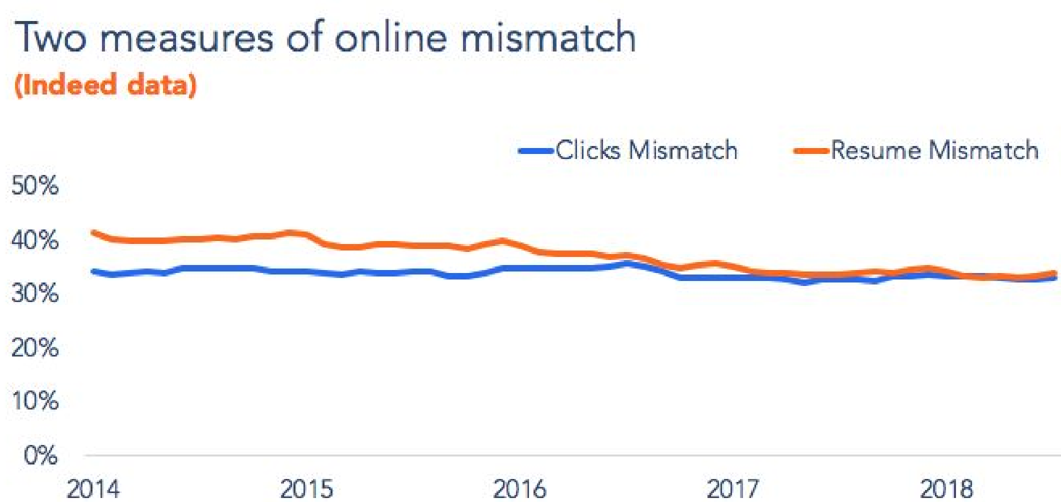
We have explored a number of different groupings and our results are consistent with what is expected: grouping the job titles into broader categories (Indeed's proprietary categories) results in a lower level of mismatch overall, but a similar pattern of flat to slightly down over the last 4

[12] According to Şahin et al. (2014) "...every statement about the role of mismatch should be qualified with respect to the degree of sectoral disaggregation used" (pg. 3538). Comparing across different aggregation approaches (occupation versus industry for example) and/or across different data sets can also shift the level of mismatch. We are focused less on the level of mismatch and more on the pattern in mismatch over time.

years. Limiting the analysis to only large title categories (around 740 categories) gives very similar results in both level and slope.

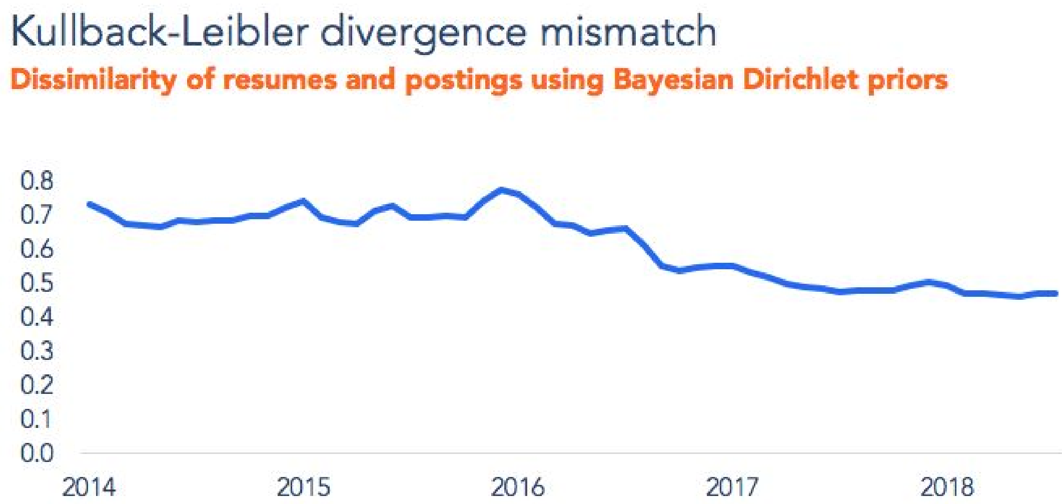
Our measure is notably smoother than LS: this may be due to the consistency of the data since our source is a common labor market with as much as possible the same definitions applied to both groups. It does not appear to be sensitive to changes in aggregation level or changes in our definition of an active job seeker. For example, if we use clicks to count active job seekers, we find very similar results for the last year or so and flat before, which leads us to emphasize "not increasing" rather than clearly declining.

Figure 3: Clicks Mismatch and Resume Mismatch



We also consider an alternative measure of dissimilarity, the Kullback-Leibler (KL) divergence measure (using Bayesian Dirichlet priors, see the recent survey by Yang, 2018, for more details on the KL divergence measure) and find broadly similar results in terms of trend some decline early but broadly flat since 2017.

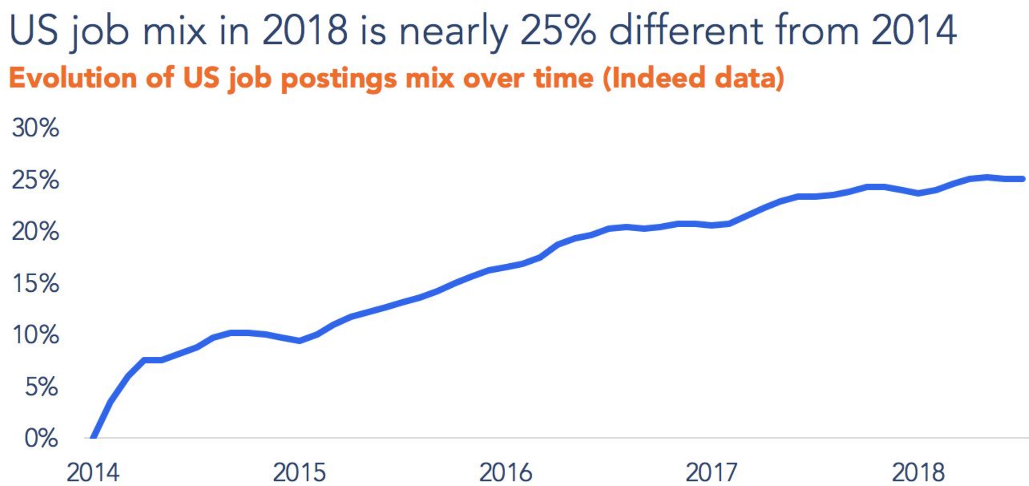
Figure 4: Robustness of Mismatch based on Kullback-Leibler Divergence



Changing job postings and changing resumes

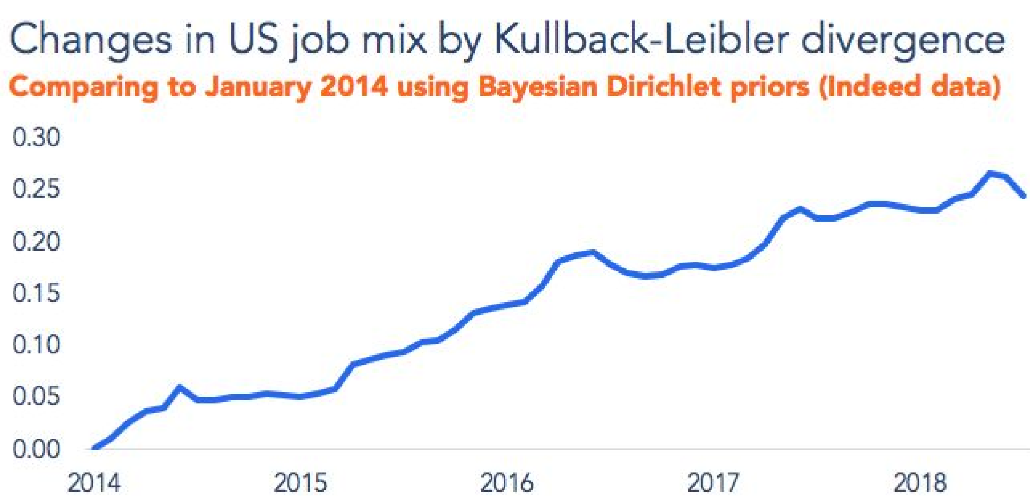
Mismatch could be flat for two reasons: either nothing is changing underneath or job seekers and jobs are adjusting to stay at a similar level of mismatch over the last several years. To examine this we used the same dissimilarity index but applied it to jobs and resumes separately over time to see how different jobs and resumes are today from what they were in 2014. What we find is that the jobs mix has changed substantially over the last few years. Comparing January of 2018 with January of 2014 (comparing January to January to exclude potential seasonal differences), our key finding is that jobs are 23.8% different in 2018 than they were just four years ago.

Figure 5: Changing Mix of Job Postings Over Time



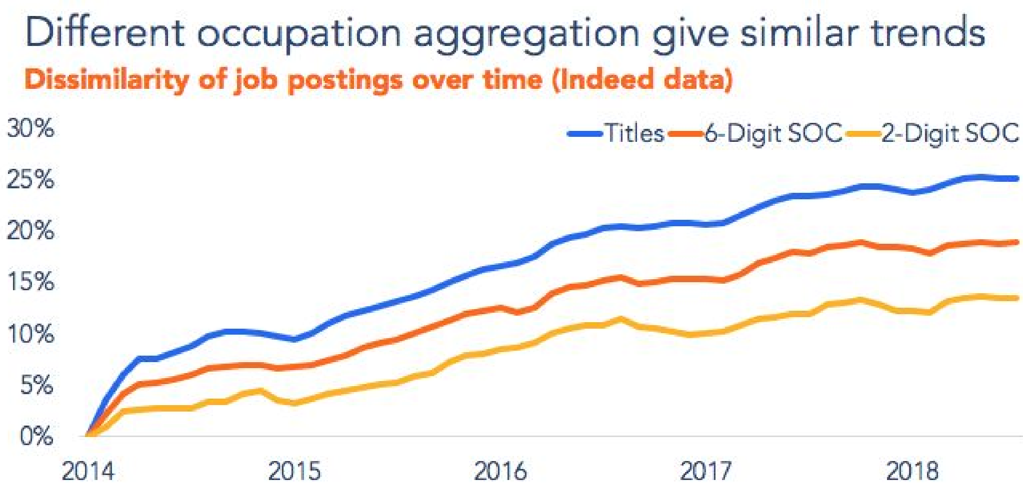
We also considered our alternative dissimilarity measure, KL divergence. The results are consistent across the two measures, with January of 2018 compared to January of 2014 having a KL statistic of 0.23 and a similar trend over the sample.

Figure 6: Robustness of Jobs Mix Changes using Kullback-Leibler Divergence



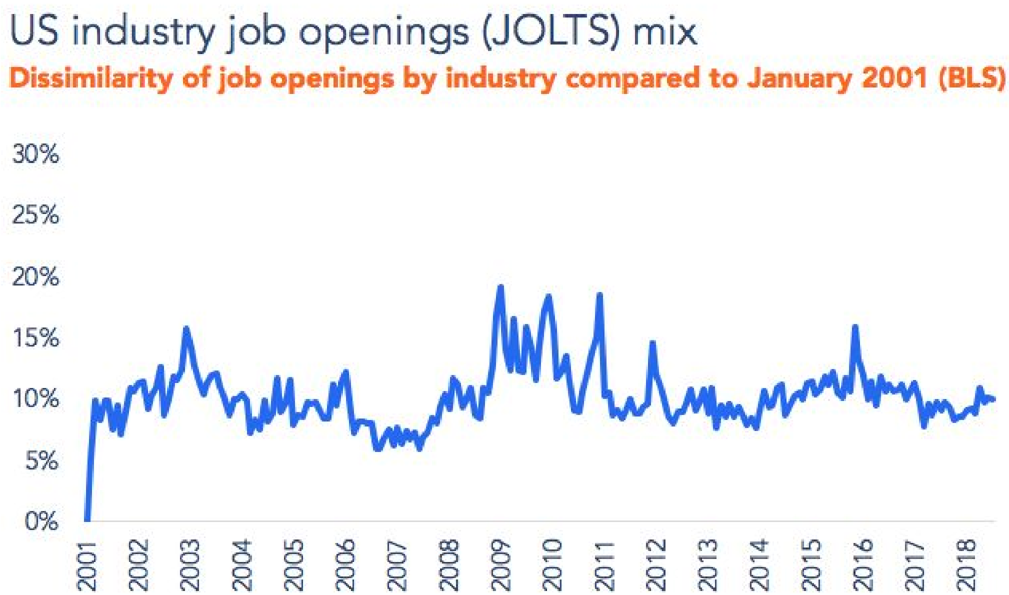
Given the sheer number of categories we have, one might think the trend in dissimilarity could be due to the amount of disaggregation. Therefore we looked at between 23 and 800 different categories based on standard occupation codes and found a similar trend, although the levels of dissimilarity compared to January of 2014 were lower which is consistent with the higher aggregation.

Figure 7: Changing Mix of Job Postings over Time for Different Aggregation Levels



Another point of context is comparing our data to data available from the Bureau of Labor Statistics (BLS). For categories we use the 12 industry categories for which we can get monthly data on unemployed and on job vacancies. With a much smaller number of categories (12 as compared to over 6000) we expect the dissimilarity to be smaller, but we might still expect an upward trend.

Figure 8: Changing Industry Mix of Job Openings over Time

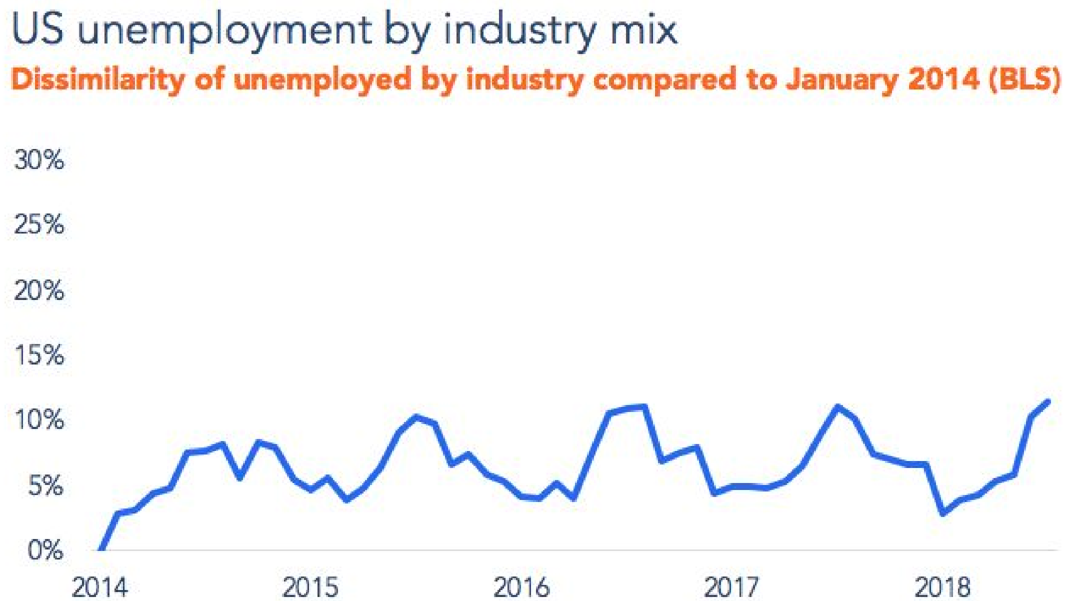


However, JOLTS is showing both lower dissimilarity in each period compared to the start date (and results are similar when comparing to January of 2014) and no upward trend. The fact that the dissimilarity is lower is likely related to the number of categories: with a smaller number of categories, we would expect the overall level of dissimilarity to be lower (e.g. in the measure above nurses vs. doctors shows up, whereas in this measure they are both under healthcare).

The fact that the trend in industry is holding steady suggests that this isn't about changes in industries, but rather about changes in who those industries are employing (the shift away from occupational therapist to pharmacy technician in healthcare for example).

Shifting to the job seeker side, similar to what we see for job postings, we see little trend by industry in the CPS data for the unemployed, but we do see an upward trend in our resume data.

Figure 9: Changing Industry Mix of Unemployed Job Seekers over Time



Resumes have, however, changed less over the past four years than job postings have. Again comparing January of 2018 with January of 2014, resumes are about 13% different than they were four years ago. One data note: because of the nature of Indeed's data, where we keep only the latest resume a job seeker has uploaded, resumes today are less comparable with resumes four years ago than job postings over the same time period. The best time period comparison is the last year, from July 2017 through July 2018, a time period over which resumes are 6.3% different, compared to job postings being 6.9% different.

Figure 10: Changing Mix of Online Resumes over Time

Robustness

We've looked at a number of different slices of the data including broad age category and the impact of including employed job seekers in our analysis.

One of the key pieces of information in the Indeed data that is not available from other sources is detailed information on employed job seekers. There is debate about how similar employed and unemployed job seekers are and what impact that might have on economic outcomes. On the one hand, Ahn and Hamilton (2016) argue that the unemployed differ in terms of relevant unobservables for job finding that vary over time and Longhi and Taylor (2014), using UK data, find that the unemployed and employed are quite different and that the differences vary over the business cycle. On the other hand, Kroft et al. (2016) find that "shifts in observable characteristics of the unemployed do not go very far in accounting for the rise in long-term unemployment." Most related to our analysis, Şahin et al. (2014) see little difference when adding in employed job seekers based on time use surveys into their measure of mismatch. Our results also find the same trend whether we limit to to just unemployed or also include the employed.

We are also able to estimate broad age categories for job seekers based on the graduation dates if they include them on their resumes. We find for this subset that mismatch is higher for young and old as compared to prime age workers, but the trends are similar for all three groups as the overall ones reported here.

Next Steps

This paper reports initial analysis of the data we have on online job postings and job search. We can (and are currently working on) look at more granular slices, e.g. by state. Mismatch by states to allow us to look at more business cycle variation. Admittedly states aren't ideal for local labor market analysis and we'd like to look at metro areas as well, but given the needs for data quantity and relevant publicly available data, we'll do a fair bit of analysis by state. We want to explore a range of relationships between economic outcomes and mismatch.[13]

The Role of Job Switchers: Our analysis is currently binary: same or not same. One concern about grouping job seekers into categories is that job seekers may not stay in the same category and that skills may be transferable across categories and/or job seekers may develop new skills over time that might lead them to change categories. This may be particularly true of the finer categories we use at the normalized job title level. Furthermore, people may have the skills for jobs, but be uninterested in doing them (interest mismatch as compared to skills mismatch). Hobijn (2012) combined data from the CPS, JOLTS, and state-level job vacancy surveys and found that the "majority of job openings in all industries and occupations are filled with persons who previously did not work in the same industry or occupation." Sinclair (2014) and Flowers (2018) have both examined the behavior of job seekers using Indeed to search for jobs in categories other than their most recent employment and find substantial amount of searching across even very broad categories. They also each document that specialization and pay are both positively related to retention by job type. This analysis suggests we may want to weight by some measure of skills and/or interest overlap for our mismatch index. In that case we may be able to think about the distance between normalized job titles and estimate a smaller amount of mismatch if in "adjacent" job titles by occupation grouping. A related approach was used by Şahin et al. (2014) to allow their unemployed job seekers to search in a new industry/occupation, but they find that the "bulk of unemployed workers keep searching in their previous employment sector" (page 3559) so their estimate of mismatch unemployment is little affected. We can also rank order the normalized titles by estimated average salary to construct a weighted variant of the dissimilarity index called the Earth Mover's Distance (Rubner et. al, 2000; for an application to the labor market see Rim, 2018).

Estimating a Natural Rate of Mismatch: With our estimates only available for a recovery period, we have little business cycle variation to estimate what is trend and what is cycle, but based on connecting our results to those of Lazear and Spletzer (2012b) we have a few initial thoughts. We see a slight downward trend in our mismatch which is consistent with the Lazear and Spletzer (2012b) interpretation that mismatch goes down as labor markets improve. We

[13] For example, Wiczer (2015) argues that occupation-specific shocks are important for understanding the pattern of unemployment duration over the business cycle

expect there to be more information along these lines once we have state level mismatch measures and can compare to somewhat varied state-level economic conditions.

Other Thoughts: Besides overlapping categories, it may be interesting to zoom in not just on narrower geographies, but also on mismatch within occupation categories or by other features of the job seeker. For example we can look at long term versus short term unemployed in a similar way to the breakdowns we've done for employment status and age categories. Indeed also has data for over 60 countries with broadly similar data collection and structure, so we plan to build indexes that are comparable across countries.

References

Abraham, Katharine G. "Is skill mismatch impeding US economic recovery?." ILR Review 68, no. 2 (2015): 291-313.

Ahn, Hie Joo, and James D. Hamilton. Heterogeneity and unemployment dynamics. No. w22451. National Bureau of Economic Research, 2016.

Cappelli, Peter H. "Skill gaps, skill shortages, and skill mismatches: Evidence and arguments for the United States." ILR Review 68, no. 2 (2015): 251-290.

Canon, Maria, Chen, Mingyu and Marifian, Elise, (2013), Labor mismatch in the Great Recession: a review of indexes using recent U.S. data, Review, issue May, p. 237-272, https://EconPapers.repec.org/RePEc:fip:fedlrv:y:2013:i:may:p:237-272:n:v.95no.3.

Duncan, Otis Dudley, and Beverly Duncan. "A methodological analysis of segregation indexes." American sociological review 20, no. 2 (1955): 210-217.

Faberman, Jason, and Marianna Kudlyak. "What does online job search tell us about the labor market?." FRB Chicago Economic Perspectives 40, no. 1 (2016).

Faberman, R. Jason, Andreas I. Mueller, Ayşegül Şahin, and Giorgio Topa. Job search behavior among the employed and non-employed. No. w23731. National Bureau of Economic Research, 2017.

Flowers (2018) https://www.hiringlab.org/2018/03/29/top-jobs-people-dont-leave/

Galaasen, Sigurd Mølster and Andreas Kostøl. "Mismatch and the Consequence of Job Loss" Presentation at the 2018 Symposium for Nonlinear Dynamics and Econometrics

Hobijn: FRBSF Working Paper http://www.frbsf.org/economic-research/publications/working-papers/2012/wp12-09bk.pdf

Karmel, Tom, and Maureen MacLachlan. "Occupational sex segregation—increasing or decreasing?." Economic Record 64, no. 3 (1988): 187-195.

Kroft, Kory, Fabian Lange, Matthew J. Notowidigdo, and Lawrence F. Katz. "Long-term unemployment and the Great Recession: the role of composition, duration dependence, and nonparticipation." Journal of Labor Economics 34, no. S1 (2016): S7-S54.

Kuhn, Peter, and Hani Mansour. "Is Internet job search still ineffective?." The Economic Journal 124, no. 581 (2014): 1213-1233.

Lazear, Edward P., and James R. Spletzer. The United States labor market: Status quo or a new normal?. No. w18386. National Bureau of Economic Research, 2012a.

Lazear, Edward P., and James R. Spletzer. "The United States labor market: status quo or a new normal?." In Proceedings-Economic Policy Symposium-Jackson Hole, pp. 405-451. Federal Reserve Bank of Kansas City, 2012b.

Longhi, Simonetta, and Mark Taylor. "Employed and unemployed job seekers and the business cycle." Oxford Bulletin of Economics and Statistics 76, no. 4 (2014): 463-483.

Patterson, Christina, Ayşegül Şahin, Giorgio Topa, and Giovanni L. Violante. "Working hard in the wrong place: A mismatch-based explanation to the UK productivity puzzle." European Economic Review 84 (2016): 42-56.

Rim, Nayoung. The Effect of Title IX on Gender Disparity in Graduate Education. February 2018 Manuscript.

Rubner, Yossi, Carlo Tomasi, and Leonidas J. Guibas. "The earth mover's distance as a metric for image retrieval." International journal of computer vision 40, no. 2 (2000): 99-121.

Şahin, Ayşegül, Joseph Song, Giorgio Topa, and Giovanni L. Violante. "Measuring mismatch in the US labor market." Manuscript, revised March (2011).

Şahin, Ayşegül, Joseph Song, Giorgio Topa, and Giovanni L. Violante. "Mismatch unemployment." American Economic Review 104, no. 11 (2014): 3529-64.

Sinclair (2014) https://www.indeed.com/hire/hiring-lab/March-2014.pdf

Smith, Jennifer C. "Unemployment and Mismatch in the UK." In Bank of England/Institute of Macroeconomics conference on ‘Unemployment, productivity and potential output: the aftermath of the crisis. 2012.

Turrell, Arthur, Bradley Speigner, Jyldyz Djumalieva, David Copple, and James Thurgood. Using job vacancies to understand the effects of labour market mismatch on UK output and productivity. No. 737. Bank of England, 2018.

Watts, Martin. "How should occupational sex segregation be measured?." Work, Employment and Society 6, no. 3 (1992): 475-487.

Watts, Martin J. "A critique of marginal matching." Work, Employment and Society 8, no. 3 (1994): 421-431.

Watts, Martin. "Occupational gender segregation: Index measurement and econometric modeling." Demography 35, no. 4 (1998): 489-496.

Wiczer, David. "Long-Term Unemployment: Attached and Mismatched?." Federal Reserve Bank of St. Louis Working Paper Series 2015-042 (2015).

Yang, Jangho. "Information theoretic approaches in economics." Journal of Economic Surveys 32, no. 3 (2018): 940-960.