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Building a composite Help-Wanted Index☆

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ABSTRACT

This paper builds a measure of vacancy posting over 1951–2009 that captures the behavior of total—print and online— help-wanted advertising, and can be used for time series analysis of the US labor market.

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1. Introduction

The number of job openings, or vacancies, is an important indicator of the state of the labor market and is used extensively in policy and academic circles.[1]

The traditional measure of vacancy posting is the Conference Board Help-Wanted Index (HWI) that measures the number of help-wanted advertisements in 51 major newspapers. However, since the mid-1990s, this "print" measure of vacancy posting has become increasingly unrepresentative as advertising over the internet has become more prevalent. Instead, economists increasingly rely on the Job Openings and Labor Turnover Survey (JOLTS) measure of job openings. However, this measure is only available since December 2000 and cannot be used to contrast current labor market situations with past experiences.

In this paper, I build a vacancy posting index that captures the behavior of total—"print" and "online"—help-wanted advertising, by combining the print HWI with the online Help-Wanted Index published by the Conference Board since 2005. A key variable in this exercise is the share of newspaper help-wanted advertising in total advertising. Since this print share is not directly observable, I estimate it in two steps.

First, I combine different datasets to estimate the empirical behavior of the newspaper share over 2000–2009. The behavior of the inferred print shares suggests that the share of online job advertising follows an S-curve, a shape characteristic of the process of technology diffusion (see e.g. Comin et al., 2006).

Second, to recover the share of print advertising since the mid-1990s, I model the development of online job advertising as the diffusion of a new technology, online job posting and job search, with a Mixed Information Source Model. This model is widely used in the marketing literature (see, for example Geroski, 2000) and is remarkably successful at modeling a related phenomenon; the diffusion of the internet in the US population.

This paper is related to recent work by Fallick (2008) and Barnichon (2009), who construct a composite HWI by estimating the newspaper share from a low-frequency trend in print HWI since 1994. However, their approach strongly underestimates the print share after 2008, and misses the mid-2000s inflection in the diffusion rate of online advertising.

Section 1 describes the construction of a composite index under the assumption that an estimate of the share of print advertising is known; Section 2 presents a method to produce an estimate of that share; Section 3 presents the composite HWI; and Section 4 concludes.

2. Constructing a composite Help-Wanted Index from the share of newspaper help-wanted advertising

This section describes the construction of a composite Help-Wanted Index that combines information from the Conference Board

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[1] See Abraham (1983), Abraham and Katz (1987), Blanchard and Diamond (1989) and more recently Shimer (2005).

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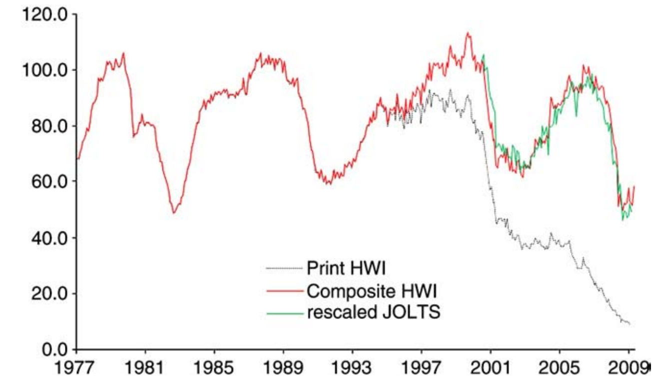

Fig. 1. Different indexes of vacancy posting, 1977m01–2009m12.

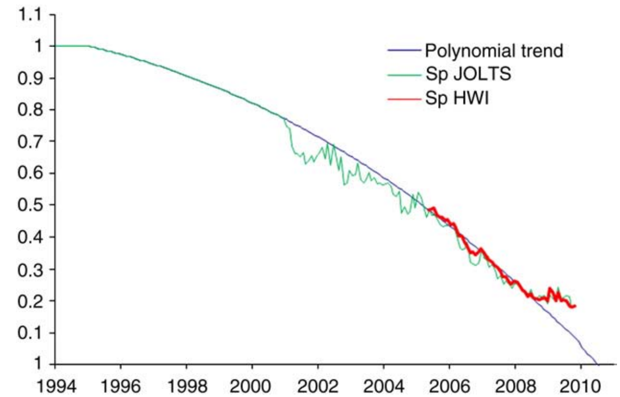

Fig. 2. The share of print advertising over 1994–2011, US data and polynomial trend.

"print" HWI available over 1951m1–2008m5 with the Conference Board "online" HWI available since 2005m5.

Denote respectively $P_t^{\#}$ and $O_t^{\#}$ the number of print help-wanted advertisements and online help-wanted advertisements. The total number of advertisements (print and online) $H_t^{\#}$ is then $H_t^{\#}=P_t^{\#}+O_t^{\#}$, and $s_t^p=\frac{P_t^{\#}}{P_t^{\#}+O_t^{\#}}$ is the share of print help-wanted advertising in total advertising. Denote H_t the composite Help-Wanted advertising index, P_t the print index, and O_t the online index. The indexes are defined with respect to some base year t_0, and I have $P_t=\frac{P_t^{\#}}{P_{t_0}^{\#}}$ and $O_t=\frac{O_t^{\#}}{O_{t_0}^{\#}}$.

I consider four separate periods:

1) Before 1995:
I assume that there is no online job posting up until 1995, which corresponds to the introduction of the World Wide Web. As a result, $H_t^{\#}=P_t^{\#}$ and I normalize the composite index so that $H_t=P_t$ over 1951–1994.
2) January 1995–May 2005:
Over that period, the print HWI is observable but the online HWI is not. However, with the share of print advertising, I can recover $O_t^{\#}$ from $O_t^{\#}=P_t^{\#}\frac{1-s_t^p}{s_t^p}$. Since $H_t^{\#}=\frac{P_t^{\#}}{s_t^p}$, starting in January 1995, I construct the composite index from $d\ln H_t=d\ln H_t^{\#}=d\ln\frac{P_t^{\#}}{s_t^p}=d\ln\frac{P_t}{s_t^p}$.
3) June 2005–May 2008:
Over that period, both the print and online HWI are available. From $H_t^{\#}=P_t^{\#}+O_t^{\#}$, I get $\frac{dH_t^{\#}}{H_{t-1}^{\#}}=s_{t-1}^p\frac{dP_t^{\#}}{P_{t-1}^{\#}}+(1-s_{t-1}^p)\frac{dO_t^{\#}}{O_{t-1}^{\#}}$. Starting in June 2005, I construct the composite index from $\frac{dH_t}{H_{t-1}}=s_{t-1}^p\frac{dP_t}{P_{t-1}}+(1-s_{t-1}^p)\frac{dO_t}{O_{t-1}}$.
4) After June 2008:
Since only the online HWI is published after June 2008, I use the fact that $P_t^{\#}=O_t^{\#}\frac{s_t^p}{1-s_t^p}$ to get $H_t^{\#}=\frac{O_t^{\#}}{1-s_t^p}$, and I construct the composite index from $d\ln H_t=d\ln\frac{O_t}{1-s_t^p}$.

3. Estimating the share of newspaper help-wanted advertising

To get a first estimate of s_t^p, I follow Fallick (2008) and Barnichon (2009), and I interpret the downward trend in print HWI (see Fig. 1) over 1995–2009 as a secular decline in print advertising due to the emergence of online advertising and the world wide web. I fit a quartic polynomial to print HWI over 1951–2009, and I estimate the print share at time t as the ratio of the polynomial's value at time t to the polynomial's value in 1994.[2] Fig. 2 plots the estimated print share.

3.1. Inferring the print share from the print and online HWIs and JOLTS data

A simple way to directly recover the behavior of the print share over 2005–2009 is to use the fact that print advertising and online advertising are simultaneously available over that period. From the definition of s_t^p, I have $O_t^{\#}=P_t^{\#}\frac{1-s_t^p}{s_t^p}$ so that after log-differencing, I can infer the behavior of $\hat{s}_t^{p,HWI}$ from

$$d\ln\left(\frac{s_t^p}{1-s_t^p}\right)=d\ln P_t-d\ln O_t. \tag{1}$$

Further, I can use JOLTS data on the number of job openings, J_t, to recover the behavior of the print share over 2000–2009.[3] I assume that the true composite index approximately comoves with the JOLTS series, so that I can write

$$\ln H_t=\ln\alpha+\ln J_t+\varepsilon_t \text{ with } \varepsilon_t\ll 1 \tag{2}$$

with $\ln\alpha$ a constant. Importantly, I will be able to verify the assumption $\varepsilon_t\ll 1$ by using the estimated share $\hat{s}_t^{p,HWI}$ as a reference point. Using the fact that $P_t=s_tH_t^{\#}$ and differencing (Eq. 2), I can infer a value $\hat{s}_t^{p,JOLTS}$ from

$$d\ln s_t^p=d\ln P_t-d\ln J_t. \tag{3}$$

Fig. 2 plots $\hat{s}_t^{p,HWI}$ and $\hat{s}_t^{p,JOLTS}$ along with the print share estimated from the polynomial trend.

Two observations are worth noting:

First, we can see that $\hat{s}_t^{p,JOLTS}$ tracks $\hat{s}_t^{p,HWI}$ remarkably well over 2005–2009. This confirms my initial assumption that the true composite HWI approximately comoves with the JOLTS series. Thus, using JOLTS data can provide valuable information on the behavior of the print share over 2000–2005.

Second, the print share does not exhibit a constant rate of decline but appears to follow an S-curve, a pattern characteristic of the process of technology diffusion (see e.g. Comin et al., 2006).[4] Thus, in the next section, I model the development of online job advertising as the diffusion of a new technology: online job posting and job search.

[2] Using an HP-filter ($\lambda=10^5$ at a quarterly frequency) instead of a polynomial produces similar results.

[3] JOLTS is produced by the BLS and contains monthly data on job openings from 16,000 establishments since December 2000.

[4] In contrast, a polynomial trend predicts an accelerating rate of decline and strongly overestimates the print share after 2008.

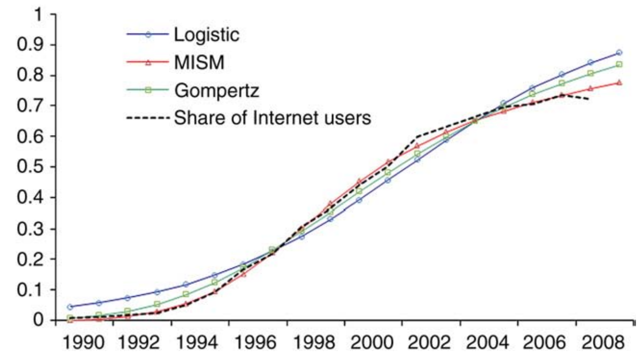

Fig. 3. Share of internet users in population, US data and model fits.

3.2. Modeling the diffusion of online job advertising

To choose an appropriate functional form for the diffusion of online job advertising, I exploit the fact that the extent of online advertising depends directly on the number of internet users. I use data from the World Development Indicators on the percentage of internet users in the US population over 1990–2008, and I assume that the diffusion of online job posting follows the same pattern as the diffusion of the internet. Fig. 3 plots the share of internet users in the US, and shows that the diffusion of the internet is asymmetric with a slower diffusion rate in the later years.

I compare the performance of three popular models of technology diffusion; the Logistic function, the Gompertz function, popularized in economics by Dixon (1980), and the Mixed Information Source Model (MISM), widely used in the marketing literature (Geroski, 2000).[5] Fig. 3 shows the non-linear least-square fits of these three models on the diffusion of the internet. Since the MISM does a very good job at capturing the diffusion of the internet, I model the share of newspaper advertising as

$$s_t^p = 1 - \frac{1-e^{-\gamma t}}{1+\alpha e^{-\beta t}} \tag{4}$$

Ideally, one would want to estimate Eq. (4) by relying only on the print share implied by JOLTS data over 2000–2009. However, Eqs. (1) and (3) only provide information on *changes* in the print share, not on the *level*. Moreover, even if the level of the print share was known for December 2000 (the beginning of JOLTS), the 2000–2009 sample is too short to estimate (4): while α and β can be precisely estimated by relying only on JOLTS data over 2000–2009, this is not the case for γ as there is not enough information to estimate the degree of asymmetry of the S-curve. To pin down γ and the degree of asymmetry, an estimate of the print share in the early stages of the diffusion process is needed.

To obtain an estimate of the level of the print share since 1995, I use two different methods. First, I use the low-frequency trend in print HWI over 1995–2000 to infer the print share over that period. Second, I rely on the existence of a strong empirical relationship between unemployment and vacancies; the Beveridge curve. I estimate a Beveridge curve over 1990–1994, the sample period immediately preceding the emergence of the world wide web, by regressing $P_t = a + bu_t + \eta_t$ with P_t the print HWI and u_t the unemployment rate. I use this equation to forecast total (print and online) vacancy posting H_t from 1995 until 2000. Assuming that the Beveridge curve did not shift over that period, I can infer an estimate of the print share from $s_t^p = \frac{H_t}{P_t}$ over 1995–2000.

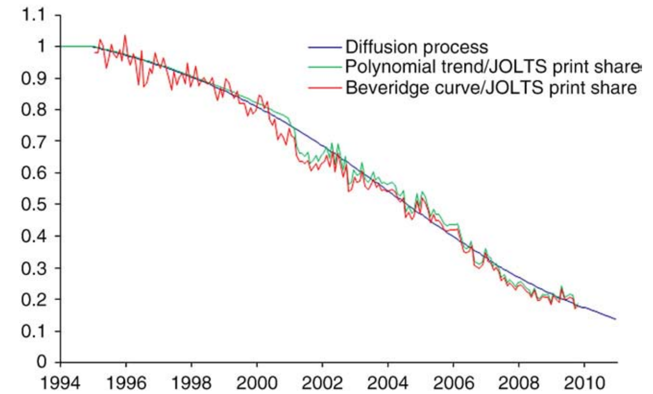

Fig. 4. The share of print advertising over 1994–2011, US data (red and green) and MISM (blue). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Fig. 4 presents the two estimated print shares. Encouragingly, the two methods provide similar estimates and indicate that using a low-frequency trend in the early stages of the diffusion process provides a reasonable estimate of the newspaper share. Accordingly, I fit Eq. (4) to the print share implied by the low-frequency trend in print HWI over 1995–2000 and by JOLTS data over 2000–2009. Fig. 4 plots the estimated MISM newspaper share, and shows that the model is very successful at capturing the decline in newspaper advertising.

4. The composite Help-Wanted Index

Fig. 1 plots the new composite HWI, along with JOLTS vacancy posting, rescaled for comparison. The two series closely track each other. In particular, the composite HWI does a good job of matching the level of JOLTS job openings over 2000–2009, indicating that the MISM can successfully model the share of online advertising.

To illustrate the interest of a composite HWI, I estimate a simple Beveridge curve equation between the unemployment rate and the job openings rate

$$\ln u_t = \alpha \ln \frac{v_t}{lf_t} + c + \varepsilon_t \tag{5}$$

using detrended monthly series over 1951–2009.[6] Fig. 5 plots the actual unemployment rate and its value predicted by the vacancy rate. Encouragingly, the composite HWI performs similarly over 1985–1994 (before the internet) and over 1995–2005.

Interestingly, in the 2008–2009 recession, the increase in the unemployment rate cannot be fully explained by the drop in vacancy posting. This indicates a very large shift in the Beveridge curve, which could reflect a cyclical phenomenon (a large increase in the job separation rate) or a structural change (such as a decrease in matching efficiency of the labor market).[7]

5. Conclusion

In this paper, I build a composite Help-Wanted Index that combines newspaper and online job advertising. To do so, I model the share of online job advertising as the diffusion of a new technology; online job posting and job search.

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[5] The logistic curve is defined by $X_t = \frac{1}{1+\alpha e^{-\beta t}}$, the Gompertz function is $X_t = e^{\alpha e^{-\beta t}}$ and the MISM is $X_t = \frac{1-e^{-\gamma t}}{1+\alpha e^{-\beta t}}$ with α, β, $\gamma > 0$. The logistic function is symmetric around its inflection point but the Gompertz and the MISM are asymmetric and allow for an adoption rate that is much faster during the initial adoption stages than the latter stages.

[6] I use an HP-filter with $\lambda = 10^7$, which approximately corresponds to $\lambda = 10^5$ (used for example in Shimer (2005)) at a quarterly frequency.

[7] Using JOLTS job openings over 2000–2009 instead of the composite HWI shows a very similar shift, indicating that this result is not due to some measurement error in the composite HWI.

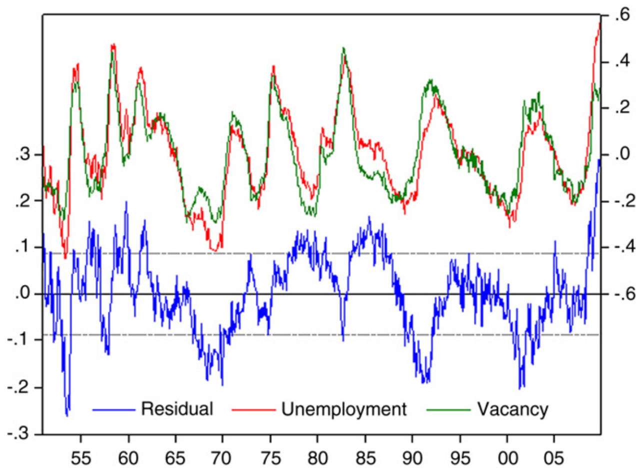

Fig. 5. Unemployment and vacancy posting, 1951–2009. Both series are detrended with an HP-filter ($\lambda = 10^7$). Residual is the difference between actual unemployment and the unemployment implied by a stable Beveridge curve.

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