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A Leading Indicator for Employment using Big Data

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Abstract

This paper uses job ad information from Peru's three main employment search websites to estimate an employment leading indicator. The information from more than 25 thousand job ads per day, posted by more than 15 thousand firms, allows us to classify ads by industry and predict the evolution of employment in the commerce, manufacturing, and services sectors. The results show that this indicator has better properties for predicting the level of employment relative to alternative models based on the mean quadratic error criterion.

Keywords: Formal Employment, Job Ads, Leading Indicator, Forecast.

Codes JEL: J64, C53, C55.

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1 Introduction

Monetary policy decisions require timely information on economic fluctuations. Appropriate economic indicators with updated information enhance the effectiveness of economic policy. Especially, indicators for the labor market are fundamental in assessing the interaction between households and firms, as well as their impact on production, productivity, income, and consumption dynamics.

Along these lines, since June 2018 the Central Reserve Bank of Peru (BCRP) publishes formal employment statistics based on the electronic payroll ("Planilla Electronica") compiled by Peru's Tax Administration Authority (SUNAT). Additionally, this source of information is classified by economic sector and labor regime (public and private). It is worth mentioning that this employment indicator has become more relevant compared to other published formal employment series, since its evolution shows consistency with the dynamics of other macroeconomic variables, such as the Gross Domestic Product (GDP), and takes into account all formal firms in the Peruvian economy.

Therefore, although the publication of new formal employment data has been crucial to the analysis of Peru's economic cycle, there is still a 45-day lag in the publication of monthly employment data. For that reason, in contrast with previous research, we use job ad information collected from specialized webs to estimate the evolution of formal employment.

The main contribution of this work is putting forward a method to forecast the number of formal jobs one quarter ahead using information from more than 25,000 daily job advertisements. The results show that our calculations using job ads until December 2019 for the manufacturing, services, and commerce sectors (which generate 70 percent of formal employment in the private sector) predict that formal employment would grow 3.9 percent in the November 2020-January 2021 quarter.

The document is organized as follows: section 2 shows the recent evolution of employment in the private sector, while section 3 presents the main contributions in the literature about short-term forecasting of labor market variables. Section 4 describes the job announcement information; and section 5 shows the methodology, results, and robustness of the proposed leading indicator of formal employment. In section 6 we perform an out-of-sample assessment to test the accuracy of the indicator. Section 7 sums up the conclusions.

2 Recent trends in Formal Employment and Information Sources

According to the National Statistics Institute (INEI), formal employment in urban areas represents 33.6 percent of the employed workforce (INEI (2019)). Specifically, formal employment in Peru engages 4.5 million workers who enjoy social benefits, pay tax obligations, and work in duly registered production units.

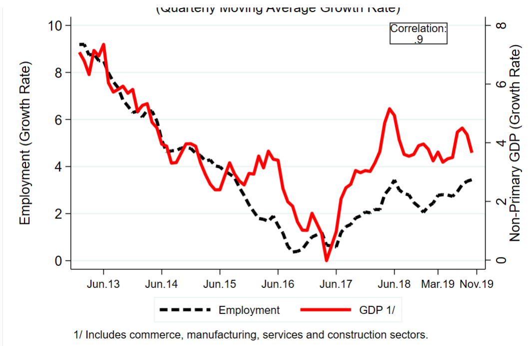
There are two main sources of formal employment data in Peru, which differ in their definition of what constitutes formal employment: the National Survey of Monthly Employment Variation (ENVME), carried out by the Ministry of Labor and Employment Promotion (MTPE); and the Monthly Electronic Payroll (PLAME), produced by SUNAT. The former is a survey carried out for a 2009 sample of 6,502 formal private firms with 10 or more workers; and the latter collects monthly payroll information from all formal companies.

In contrast with ENVME, PLAME employment information is consistent with other indicators of economic activity associated with formal employment. In this regard, the recent evolution of formal employment reported by PLAME is consistent with annual growth in the number of affiliates to Private Pension Funds (AFPs), GDP, household consumption, and income tax payroll deductions, among others. In this light, several institutions, including the BCRP, consider PLAME a better source of employment information at the national level.

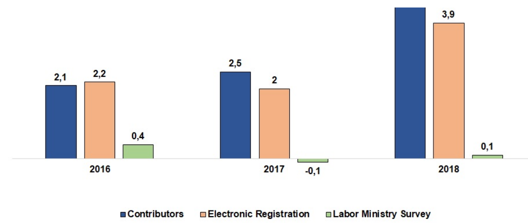
Figure 1 shows the evolution of formal employment along with other economic indicators. According to (a), formal employment growth is closely linked to the momentum of production in non-primary sectors (construction, commerce, manufacturing, electricity, and services). In particular, short-term fluctuations in these sectors have contemporary effects

Figure 1: **Formal Employment (FE) and other macroeconomic indicators**

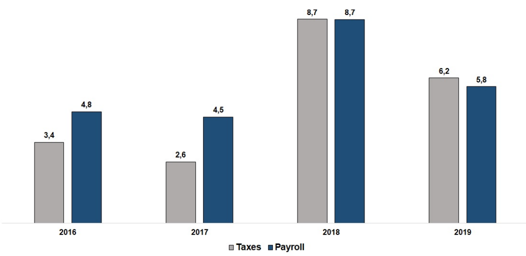
(a) FE and GDP: non-primary sectors 1/



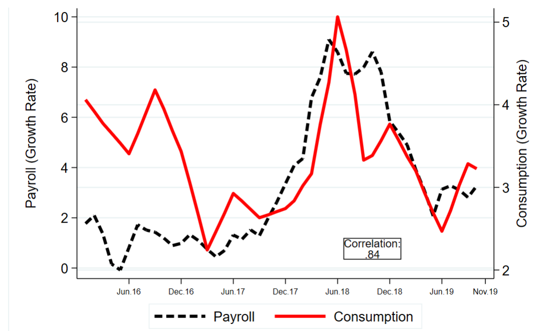
(b) FE y AFP's Contributors



(c) Payroll and Income Taxes



(d) Payroll and Real Private Consumption

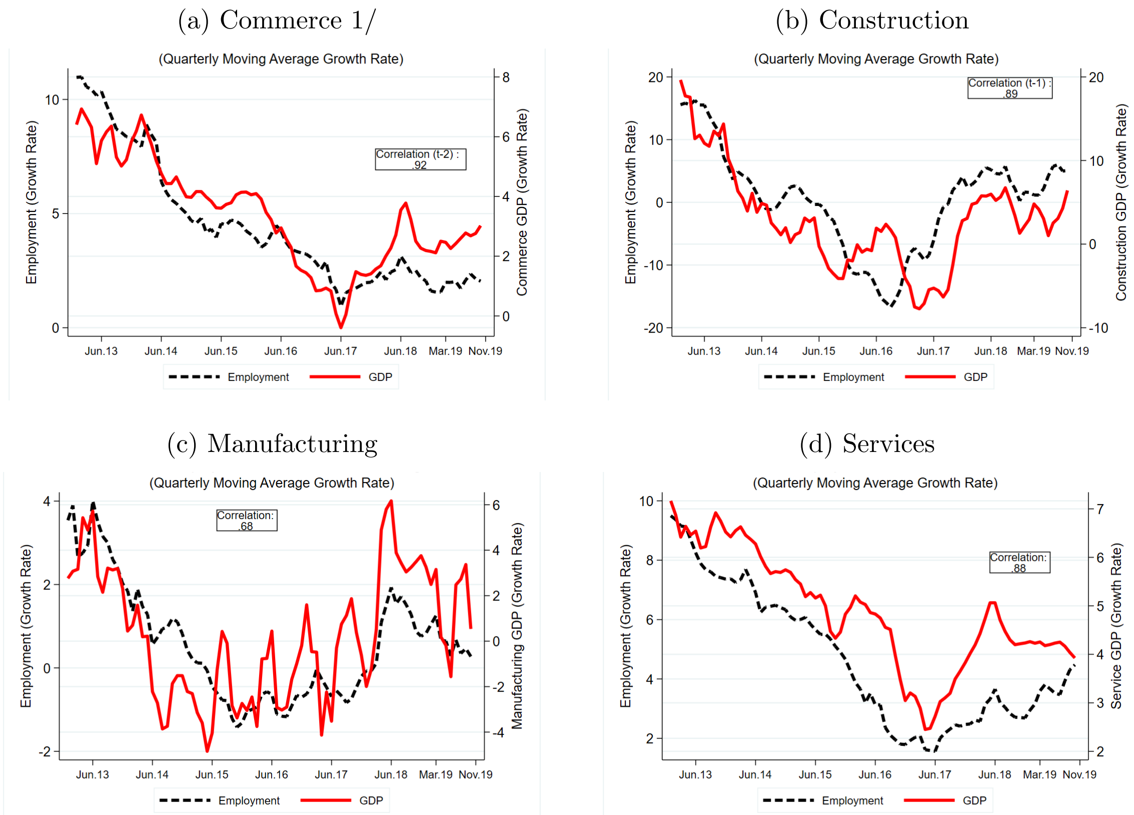


on employment. A clear example is the contraction of growth and employment during the El Niño phenomenon (FEN) in 2017, and the recovery in both variables when the FEN disturbance ended. Additionally, according to (b), the evolution of formal employment is consistent with the increase in the number of AFP contributors, a pattern that is not reflected in other employment data sources such as ENVME. Finally, other labor indicators obtained from PLAME, such as formal workers' labor income, also share the trends of other economic indicators such as income tax payroll deductions[1] and consumption, as shown in (c) and (d), respectively.

The dynamics of hiring in Peru depends on different factors, such as firms' productivity (Nordhaus (2005); Rodriguez and Higa (2010); Autor and Salomons (2017)), labor costs (Pierluigi (2008); Chacaltana (1999)), labor market rigidities, (Alexandre et al (2010)) and

[1] These taxes correspond to a percentage of employees' labor income. This percentage varies with the level of annual labor income.

Figure 2: **Formal Employment and GDP of non-primary sectors**



other structural features of Peru's labor market, such as informality. However, cyclical fluctuations and the seasonal dynamics of formal employment in non-primary sectors is closely associated with economic activity, as reflected in Figure 1. Thus, higher production is directly linked to more employment in the short run; i.e., labor demand is the main determinant of job growth. Along these lines, Figure 2 shows that, in the case of non-primary sectors, both variables share similar short-run dynamics, with correlation coefficients above 0.85 in the commerce, construction, and services sectors; and above 0.65 in the manufacturing sector.

To understand employment dynamics at the sector level, it is essential to develop indicators that can anticipate its short-run behavior. In this regard, approximating labor demand through job announcements is an essential tool for predicting labor market performance. In fact, the use of job advertisements for constructing employment leading indicators is increasingly frequent (Harper (2012)).

Since job advertisements partially capture firms' expectations about economic performance, they become a relevant source of information about the number of jobs that will be required in the short term. Accurate estimation of employment becomes more relevant since there is a 45-day lag in the publication of monthly official employment statistics.

3 Literature Review

The use of job advertisements to predict employment performance or other economic variables is not new in the literature. For example, DeVaro and Gürtler (2018) use information from newspaper job advertisements published in 1940 to analyze job hiring processes. Similarly, Abraham and Wachter (1987) use job ads in newspapers to establish the number of job vacancies in the labor market; and, more recently, Atalay et al (2020) used newspaper job advertisements from 1950 to 2000 to analyze the evolution of employment characteristics in the U.S.

At the same time, the use of *big data* in social sciences and statistics has increased significantly in recent years. Thus, economics has not been indifferent to using these sources of massive structured, semi-structured, and unstructured data, generated exponentially through high-performance applications (Rodriguez-Mazahua et al (2015)). On the contrary, the availability of new sources of information has promoted the creation of new economic indicators and the development of new techniques to process and analyze data (Cornejo et al (2017)).

Among previous works using high-frequency indicators for estimating employment variables, the research by Chang and del Río (2013) stands out. The authors use information on job searches reported by *Google Trends* to predict the employment indexes in companies with more than 100 workers in Peru. The results of this study show that forecasts that use this kind of information are better than those that do not.

Similarly to the research done for Peru, D'Amuri and Marcucci (2010) predict the monthly unemployment rate for the U.S. using a leading indicator based on Google job searches. Despite its limited availability, this indicator is very useful for predicting the short-term dynamics of unemployment. The authors use simple regression models, finding that these models outperform others using long samples.

Other authors have also developed leading indicators to predict short-term employment fluctuations based on macroeconomic variables or Internet job searches, among others. For example, Gupta et al (2014) predict employment for eight sectors via cointegration, autoregressive, and univariate vector models using from 20 to 143 monthly economic variables, including personal income, manufacturer orders, unemployment insurance applications, etc.

Regarding direct information from website job advertisements, Turrel et al (2019) use it to analyze the British labor market through various *Machine Learning* algorithms. The authors show that website advertisements have explanatory power in predicting wages. Edwards and Gustafsson (2013) approximate the growth in the number of workers by using job advertisements from various sources, including websites.

It is worth mentioning that using job advertisements may have some limitations due to sample representativeness. Kurekova et al (2015) point out that the adjustment of sample representativeness could be challenging because the structure of the entire population of job vacancies is practically unknown in some economies. Therefore, reliability and representativeness should be assessed on a case-by-case basis, and the advertisement information should be combined with other sources of vacancy data.

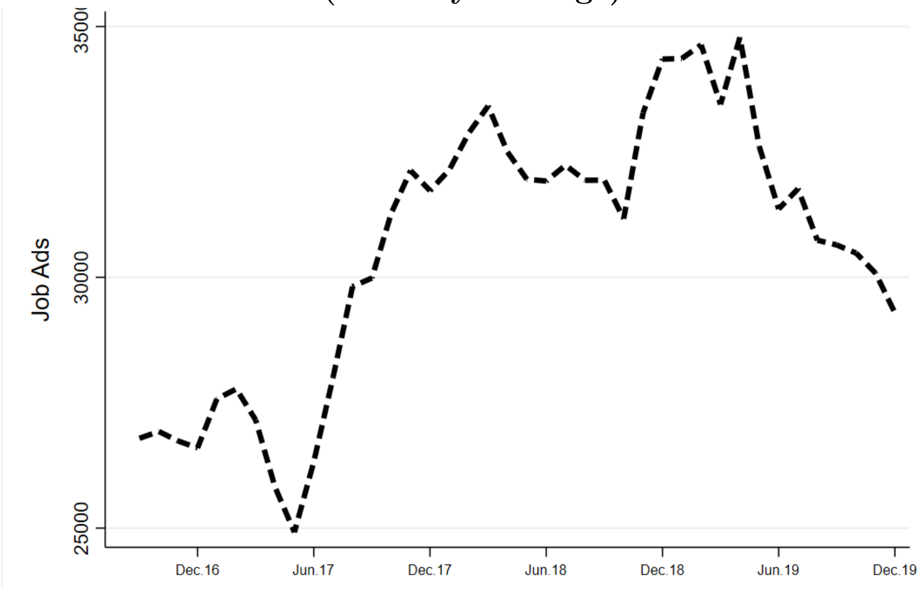
4 Employment Advertisements

4.1 Massive ads

We have used the *webscraping* algorithm written in "R" to extract information from job advertisements since September 2016. This algorithm is based on the RVEST library, widely used for these purposes. The algorithm adapts to the website architecture from which the

Figure 3: **Number of Jobs Ads**

(Monthly Average)



researcher seeks to extract information.

The detailed process is as follows: first, we identified the relevant parameters or tags (i.e., date, job offer description, announcing firm, etc.) in the job advertisement websites (Aptitus, Bumeran, and Computrabajo) that we use for the daily report of advertisements.[2] Second, we establish a connection using the URL and then we use the RVEST framework to extract the data through the tags and the HTML nodes.[3] Finally, we process and store the extracted information in the dataframe using formats corresponding to the day of download.

Based on the downloaded advertisements, Figure 3 shows a four-week moving average of the number of daily job advertisements with less than seven days from publication. The number of job announcements shows an increasing trend from May 2017, one month after the highest FEN negative impact. The expansion continued until the end of the first quarter of 2019, when the labor market cooled down. The contraction of the number of announcements reflects growth moderation in sectors that had been leading economic expansion, such as the

[2]Queries are made in XPath, CSS and HTML nodes so as to narrow down the content set by ads.
[3]Some features are filtered using the Google Chrome SelectorGadget extension.

agricultural-export industry and the services linked to it.

4.2 Ads by sector and firm size

To classify job advertisements by economic sector and firm size, we use the names of the formal firms that advertise on job platforms (more than 15 thousand companies with a Taxpayer Identification Number (RUC)). Using RUCs it is possible to match firms with a dataset containing information on all formal firms in Peru, such as number of workers and industry. According to Table 1, the number of companies with more than 5 and 10 workers was 80,332 and 38,458, respectively, in 2017. We find that at least 9,000 of these firms announced job vacancies through websites in 2017.

Table 1: **Announcing firms and total number of firms classified by the number of workers , 2017**

Sector	# of firms announcers	# of firms with 5 or more workers	# of firms with 10 or more workers
Agriculture	95	1954	1198
Commerce	1940	15826	7110
Manufacturing	1250	9161	4764
Services	5161	38573	19504
*Others	480	14818	5882

*Includes other sectors such as mining, construction, fishing and unclassified firms.

Based on this classification, Figure 4 reflects that formal firms with 10 or more workers showed an increasing trend in the number of advertisements until reaching an inflection point in April 2019.

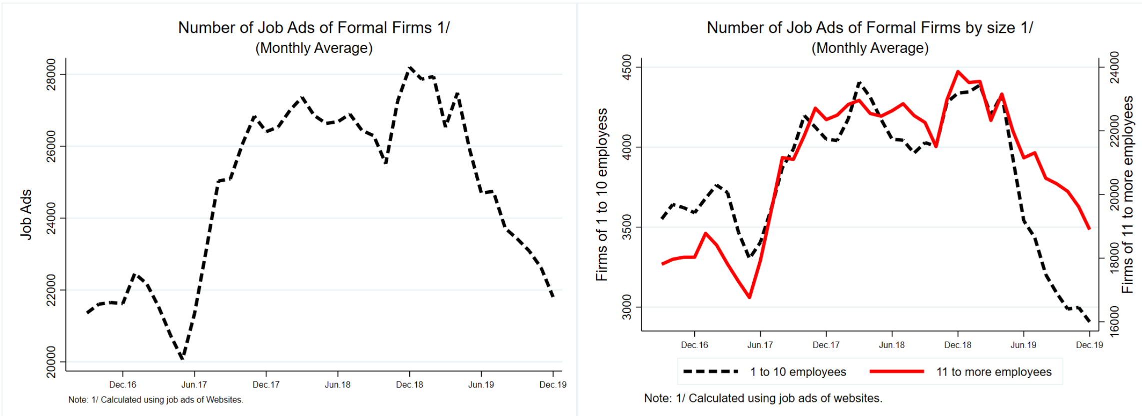
5 A Leading Indicator for Formal Employment

Along these lines, we construct an indicator using the total number of ads by economic sector from all job posting platforms (eliminating repeated ads).

In order to be able to use job announcements as a leading indicator of formal employment

Figure 4: **Number of Job Ads by Firm Size**

(a) Total (b) by Firm Size



published in the *Planilla Electronica*, we compare the cycle of each employment series with the cycle of job ads. We use the Baxter and King (BK) filter to calculate the employment and job announcement cycles (gaps). According to Figure 5, labor demand by formal firms, proxied by the cyclical component of job advertisements, would lead the employment cycle by one-two months for the services, commerce, and manufacturing sectors. These sectors absorb almost 70 percent of total formal jobs in the economy.

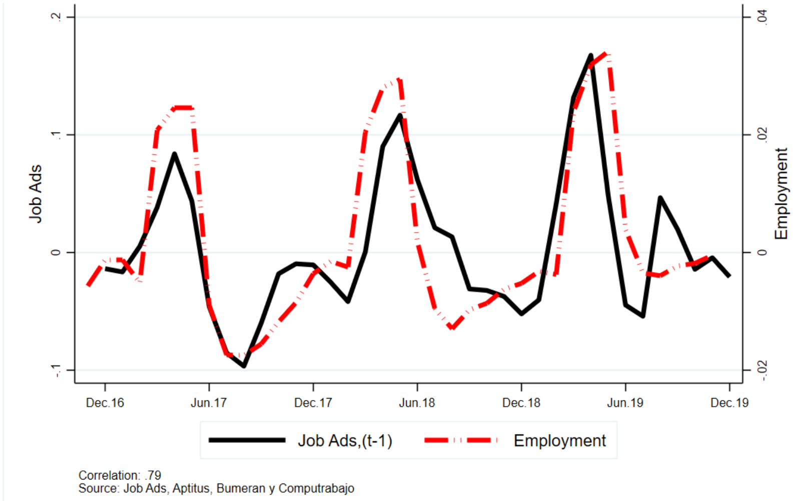
We use the employment advertisement gap as a robust indicator of labor demand, considering that entry/exit or mergers of current employment ad platforms may occur. Because of the appearance/closure of platforms, the information on the number of advertisements could be more sensitive than the information on gaps. Additionally, some job advertisements omit information on firms, which reduces the number of identified ads actually posted by formal firms. This affects the calculation of the number of ads by sector, thereby increasing the volatility of the series. For this reason we choose the gaps as a better measure.

5.1 Methodology and estimation

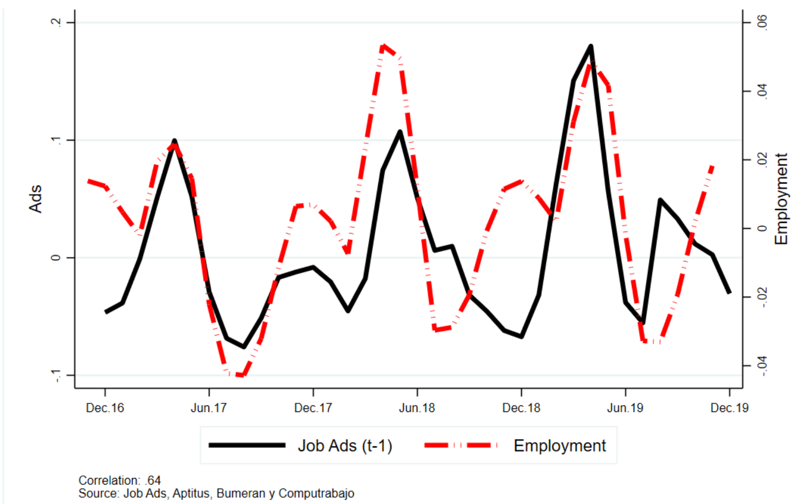
In order to estimate employment by sector, each employment series, (y_t), is decomposed into three components: cycle, (c_t); trend, (τ_t); and seasonality f_t. As shown in equation 1, we

Figure 5: **FE and Job Advertisement Gaps by Economic Sector**

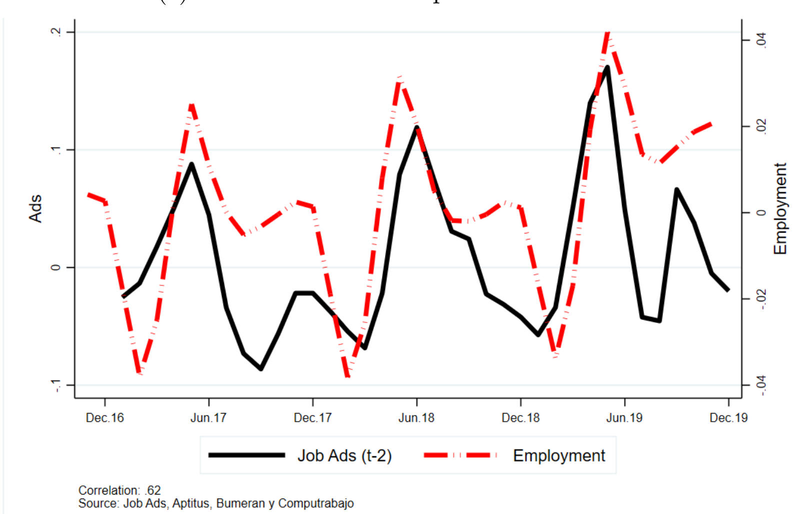
(a) FE and Job Ads Gaps: Commerce Sector



(b) FE and Job Ads Gaps: Manufacturing Sector



(c) FE and Job Ads Gaps: Services Sector



assume a multiplicative seasonal factor, f_t for the employment series.

$$y_t = y_t^{sa} \times f_t, \tag{1}$$

where

$$y_t^{sa} = (\tau_t + c_t),$$

and

$$\gamma_t = (c_t/\tau_t) \times 100.$$

We take into account the number of holidays and leap years in the entire sample to construct the seasonal component, f_t. Finally, the trend, τ_t, and the cycle, c_t, make up the seasonally adjusted series,y_t^{sa}, whereas γ_t denotes the gap for each series.[4]

In the case of the sectors whose job advertisement cycle is highly related to the employment cycle, we estimate a linear regression between both variables. Then, based on this estimated relationship and the available job announcement information, we estimate the formal employment gap in each sector for the following months.

Formally, and following equation 2, we estimate a linear regression of γ_t on ADS_{t-i}, which represent the employment and job announcement gaps, respectively. In this case , the subscript i denotes the number of months by which advertisements lead the employment cycle. In both cases, γ_t and ADS_{t-i} are expressed as the percentage deviation from their trends.[5] In this case, the estimated parameter β_2 captures the direct relation between the number of job ads and the gap in the number of jobs for each sector.

$$\gamma_t = \beta_1 + \beta_2 ADS_{t-i} + \varepsilon_t \tag{2}$$

[4]After calculating the seasonal component, and prior to calculating the cyclical component, each employment series is projected for 24 periods through the best ARIMA model to avoid the end-of-sample problem.

[5]For example, in the case of calculating the employment gap $\gamma_t = (c_t/\tau_t) \times 100$.

In the case of employment in the commerce sector, job ads anticipate employment outcomes by one month. The relatively short hiring times in this sector are likely associated with the less specific average skills required. Finding workers with less specific skills is associated with shorter hiring processes, while longer hiring times are linked to the need for more experienced (expensive) workers.[6] For other economies such as the U.S., the estimated average hiring time in the commerce sector is around 25 days (DHI (2017)).

In the case of formal employment in manufacturing, the job advertisements gap leads the cycle of the employment gap by one month. It is worth mentioning that the time needed to fill a vacancy and the recruitment intensity varies according to the size of the company and the recruitment methods by industry (DHI (2017)).

Finally, in the case of the services sector, job ads lead the employment gap by up to two months. According to international evidence, the contracting period varies depending on the type of service. For example, in the case of the U.S., the average period for financial, medical, and other services is 44.7, 49, and 31.2 days, respectively (DHI (2017)). The fact that the average time for filling a vacancy in Peru is longer than in the U.S. may be partially explained by the existence of greater labor frictions.

Once we obtain an employment gap forecast for each sector, $\hat{\gamma}_t$, we estimate the number of seasonally adjusted jobs, $\hat{y}_t{}^{sa}$, using the estimated trend, τ_t. Finally, we calculate the employment levels $\hat{y}_t$ after applying the seasonality factors, f_t.

5.2 Results

Figure 6 shows the annual percentage change of the observed and estimated (projected) employment series for different sectors. The red (dotted) line denotes the percentage change of the estimated series, while the black line denotes the percentage change of the number of workers in each sector. All the estimated series show that predicted employment closely follows the evolution of the employment series. At the same time, according to the recent

[6] Reducing the risk of making hiring mistakes requires investing a longer search time (DHI (2017)).

evolution of job ads, the employment performance for the following months varies by sector.

In the case of the commerce sector, the model predicts an employment growth of 2.1 and 2.3 percent for November and December 2019, respectively. This growth is above the average for the last 12 months (1.9 percent). The case of manufacturing is different, since the model predicts slightly negative or null growth for the last months of 2019. This forecast would intensify the slowdown of the sector in the last 18 months. Finally, the model predicts an employment growth in the service sector of 4.0 and 3.6 percent for November and December 2019.

Adding up the sector-level information, Figure 7 shows the projection of employment growth for the three main sectors, which account for 70 percent of formal private employment. According to the estimates, employment growth in this group would be around 2.8 percent, slightly below the average for the last 12 months.

Finally, to estimate total formal private employment it is necessary to have a projection of the level of employment in the remaining sectors. To do this, we estimate the number of workers in the fishing, mining, agricultural, electricity and water, and construction sectors for the following months,[7] estimating the best ARIMA model for each sector. Finally, we aggregate the employment forecasts for the commerce, services, and manufacturing sectors with those for the remaining sectors. The result is shown in Figure 7 (b), which indicates that private formal employment growth in November and December 2020 would be around 3.9 and 4.0 percent.

5.3 Robustness for unobservable variables

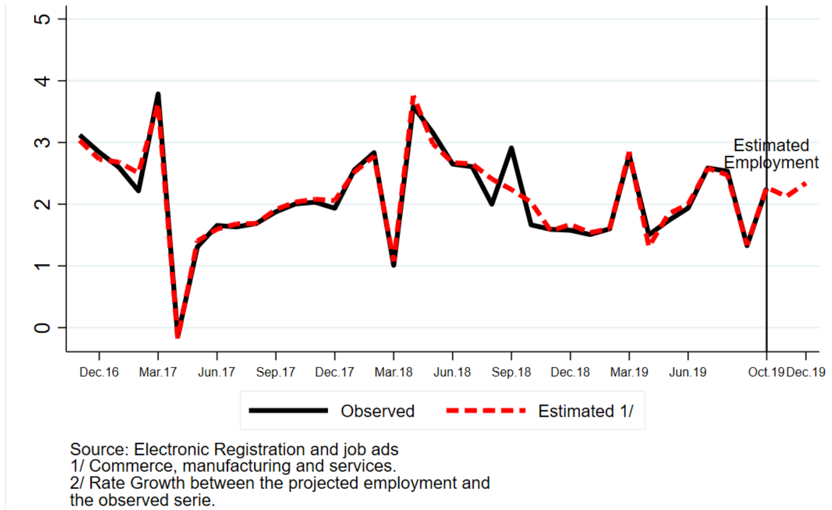
An important element that must be considered in applying this methodology is the robustness of unobservable variables. In this case, the results will depend on the filter used to estimate the employment cycle. Along these lines, we compare our initial results with the estimations resulting from applying the Hodrick-Prescott filter.[8]

[7]We also estimate employment for firms that have not been classified in any specific sector.

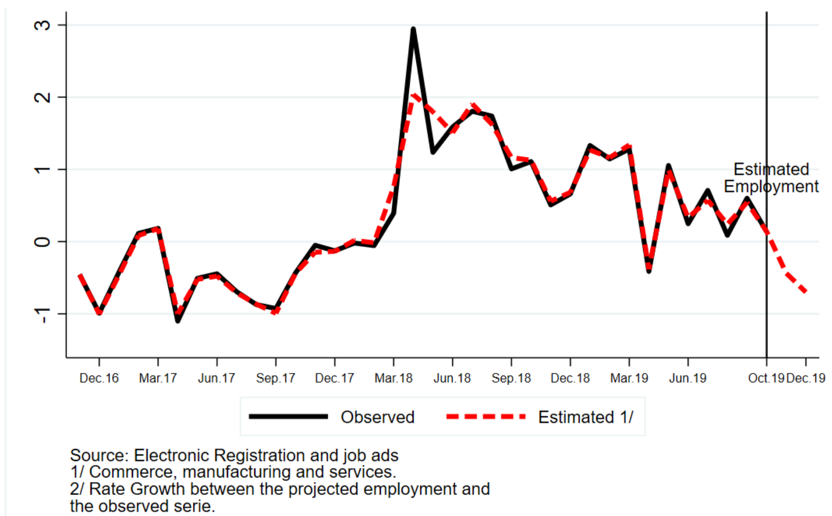
[8]We calibrate a smoothing parameter of 14,400 for monthly series and 270,400 for weekly series.

Figure 6: **Estimation of FE by Economic Sector (Growth rate)**

(a) Commerce



(b) Manufacturing



(c) Services

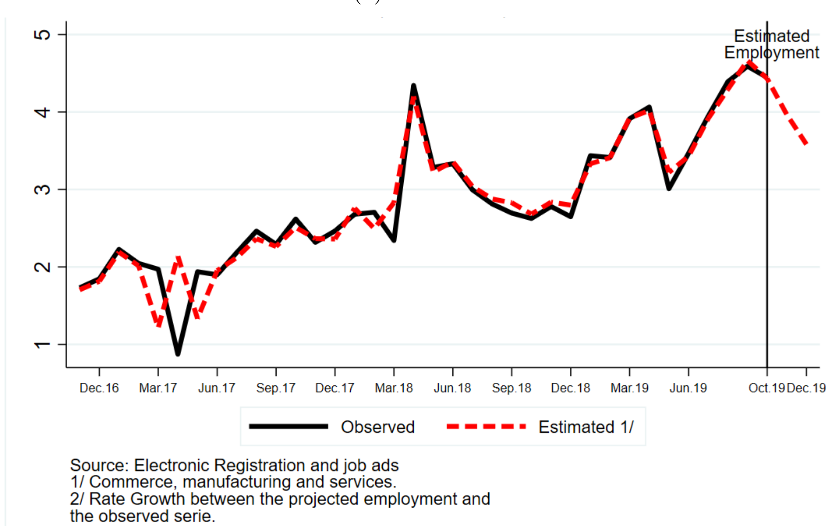
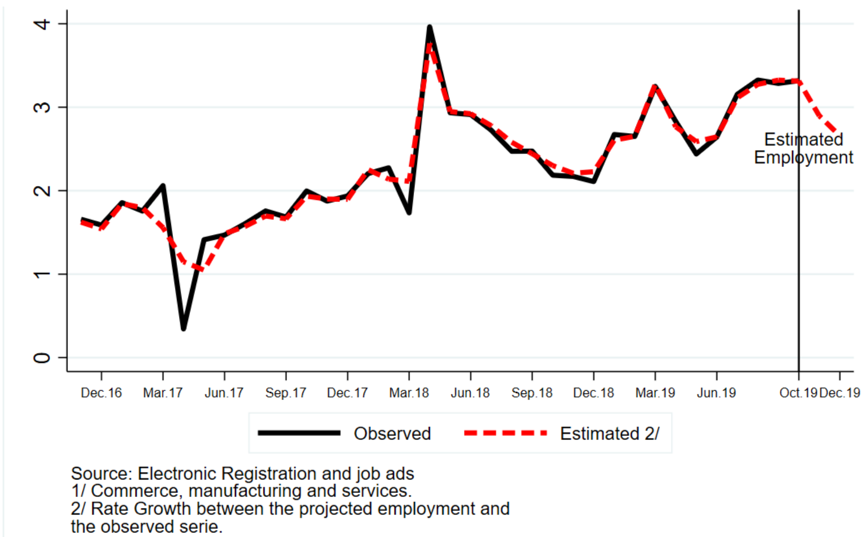


Figure 7: **Aggregated Forecast of Formal Employment (Growth rate)**

(a) Main Sectors



(b) Total

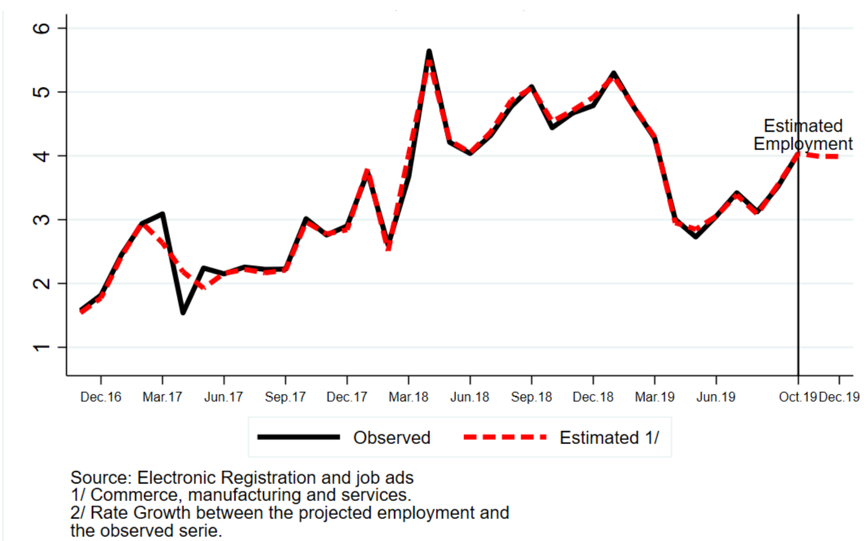


Figure 8 shows the results of both estimations. The forecasts for the employment series using both filtering methods do not show large differences over the projection horizon (0.2 percent difference on average). However, we should emphasize that, even though the results obtained using both filters are similar, the BK filter generates a one-month information loss. This constraints the projection by up to two months at most. However, the estimation of formal employment growth using the BK filter closely follows the path of employment within the sample.

6 Forecast Assessment

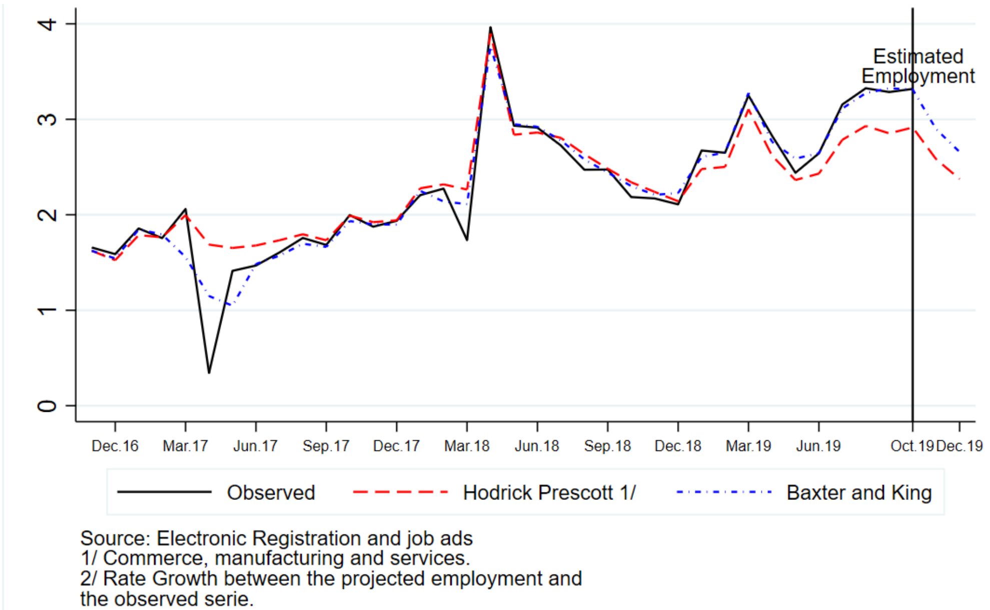
To assess the accuracy and the gains of including job ads as a short-run employment predictor, we perform out-of-sample forecasts of the estimated model and compare the accuracy of these estimates with those obtained from the autoregressive models. To this end, we estimate the employment cycles, but truncating the sample month by month from February 2018 to the last available data in the *Planilla Electronica* (October 2019). Using the leading information on job announcements we can estimate the level of employment up to the next three months. This exercise is repeated consecutively, month by month, up to one month before the end of the sample. Equivalently, the same process is carried out, but estimating an autoregressive model - AR (1) - and forecasting up to three months ahead.

The predictive capacity of each model can be compared for different horizons (one, two, or three months ahead). Given the data availability, there are 20 observations to evaluate the one-month horizon; 19 observations to test a two-month forecast; and 18 observations in the case of a three-month forecast.

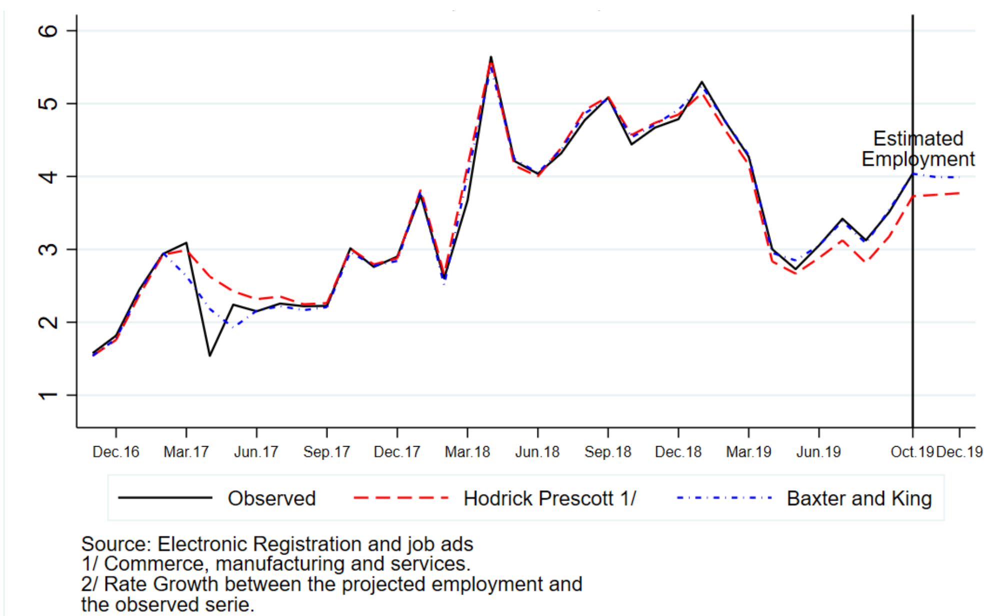
We repeat the same process to assess the robustness of the previous results, but using the Hodrick-Prescott (HP) filter to estimate the gaps for the same variables. It should be noted that using the BK filter only allows forecasting up to two periods, because one observation is lost during the cycle and trend estimation process. In addition, we also estimate an

Figure 8: **Out of Sample Forecast of Private Formal Employment (Growth rate)**

(a) Main Sectors



(b) Total



AR-ads model, which incorporates information from job announcements in addition to the autoregressive component of employment growth.[9]

Table 2 reports the average absolute differences between the predicted and observed data for each model. The results of the one-period forecast indicate that the model that uses exclusively the employment ads gap, estimated from the BK filter, Ads (BK), produces an average absolute error of 0.36 percent. This value is five times lower than the average error of the autoregressive (AR) model, and even lower than the model that contains an autoregressive structure and the job ad data, AR-Ads. Likewise, comparing the Ads (BK) model with the one that uses the HP filter, Ads (HP), the average absolute error of the former is also lower, but the standard deviation is lower in the Ads (HP) model.

Table 2: **Out of Sample Evaluation**

Model	**Mean**	**S.D**
1-period forecast		
Ads (BK)	0.36	0.63
Ads (HP)	0.54	0.49
AR	1.62	1.2
AR-Ads	0.62	0.8
2-period forecast		
Ads (BK)	1.9	0.89
Ads (HP)	2.1	0.9
AR	1.7	1.2
AR-Ads	0.69	0.8
3-period forecast		
Ads (HP)	1.5	4.1
AR	1.7	1.16
AR-Ads	0.57	0.58

The results are different for the two-period forecasting horizon. The Ads (BK) model slightly underperforms relative to the AR model, while Ads (HP) is the least performing specification. However, when we include job ad information in the autoregressive model (AR-Ads model), the average error significantly diminishes to less than half (from 1.7 to

[9]The specification of this model is the following: $\Delta y_t = \beta_1 + \beta_2 : \Delta y_{t-1} + \beta_3 ADS_{t-i} + \varepsilon_t$.

0.69).

Finally, in the three-period-ahead forecast we are limited to estimating a model using the HP filter. This model shows a slight advantage over the AR model, erring up to 0.2 percent less on average, but with a standard deviation up to four times greater. Nevertheless, the projections improve significantly when we also incorporate information from job ads in the autoregressive model, thereby reducing the average error from 1.7 to 0.57 percent.

Summing up, model forecasts that only use information from job advertisements have better properties than autoregressive models in the short term for certain periods. However, when information on job announcements is included in an autoregressive model, it usually becomes the one with the best properties for projection horizons two and three months ahead. These specifications report significantly lower absolute deviations than the alternative specifications.

7 Conclusions

This article uses information from job advertisements published on websites to estimate and forecast formal employment in Peru. With information from more than 25 thousand weekly job announcements, we estimate the short-term employment performance in the commerce, services, and manufacturing sectors. In particular, the job announcement cycle leads the formal employment cycle by 60 days in the services sector and by 30 days in the commerce and manufacturing sectors. Then, based on the estimated cycles, we project the level of employment in these sectors, which explain around 70 percent of Peru's formal employment.

To test the usefulness of this indicator, we perform out-of-sample evaluations. We find that models that include information from job advertisements show greater short-run (one, two, and three months) accuracy than the best autoregressive models.

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