The Labour Market Effect of Fiscal Policy Uncertainty†

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Abstract

This study examines the effect of fiscal policy uncertainty (FPU) on job searches and labour demand in the United States. We first develop search-based job search indices and find that increased FPU leads to lower job search levels. At the same time, when FPU rises, labour demand is also reduced. The effect of FPU varies across different regions and is also affected by the prevailing monetary policy stance and the level of government debt. Labour market institutions can help explain these differences. Lastly, FPU reduces matching efficiency in labour markets. These results are robust to alternative specifications, the consideration of the effect of uncertainty from risk, and the endogeneity problem.

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1 Introduction

Investors, researchers, and policymakers have analysed the 2007–09 global financial crisis and the subsequent political events from the perspective of policy uncertainty and its effects on the economy. Fiscal policy uncertainty (FPU) is considered harmful for the economy.[1] The Philadelphia Fed's July 2010 Business Outlook Survey reported that 52 percent of firms surveyed cited 'increased uncertainty about future tax rates or government regulations' as one of the causes of their sales decline.[2] FPU hampers recovery from recession (IMF, 2012) and is repeatedly cited as a concern for respondents to the Fed's Beige Book, a qualitative report which is published by the US Federal Reserve and aims to provide an overview of federal bank stakeholders' positions regarding the economic conditions in their respective economies.

Many researchers have attempted to estimate the effect of policy or political uncertainty on the economy. Alesina and Tabellini (1989) examine the relationship between political instability, external debt, and capital flight, demonstrating that capital flight tends to occur during a period of high political instability and that political instability incentivises governments to accumulate external debt. Rodrik (1991) investigate the effects of policy uncertainty on private investment in developing countries and show that even a moderate amount of uncertainty can heavily impede investment. Barro (1991) and Alesina and Perotti (1996) find that measures of political instability are correlated with investment rates in an international setting. Hassett and Metcalf (1999) theoretically reveal that tax policy uncertainty could increase investment when the policy is a stationary discrete jump process, which better reflects historical changes in tax policy.

[1] There are several examples of increased fiscal policy uncertainty in the study time period, such as the federal government shutdown in October 2013 and the Tax Relief.

[2] https://www.philadelphiafed.org/research-and-data/regional-economy/business-outlook-survey/2010/bos0710

More recently, Julio and Yook (2012) use dummy variables for election events as a proxy for political uncertainty and conclude that political uncertainty leads firms to reduce investment expenditures until the electoral uncertainty is resolved. Julio and Yook (2016) use the same proxy to show that US foreign direct investment drops significantly around domestic elections. Pástor and Veronesi (2012) theoretically show that uncertainty about policy should increase volatility and correlation among stocks. Pástor and Veronesi (2013) further extend these insights by considering policy heterogeneity and show that policy uncertainty commands a risk premium; the magnitude of which is greater in weaker economic conditions. Fernández-Villaverde et al. (2015) reveal that fiscal volatility shocks have sizeable adverse effects on economic activity, while certainty about tax credits and budget adjustment encourage firms to invest. Using a text-searching technique, Baker et al. (2016) measure uncertainty as the proportion of uncertainty-related articles to total news articles and show that policy uncertainty is harmful for the economy. Caldara et al. (2020) develop a trade policy uncertainty index and show that US capital investment decreased by about 1.5% in 2018, which was the year that saw the largest increase in trade policy uncertainty. Many other empirical studies show that policy uncertainty decreases capital investment, slows down economic activity and increases unemployment (e.g. Gulen and Ion, 2016; Leduc and Liu, 2016; Hassen et al., 2019).

However, the extant literature has not investigated the effect of policy uncertainty on job searches and labour demand, though these factors are important for understanding labour markets. Search effort is a key determinant of employment, as a higher number of job matches are formed when both recruiters and job seekers make greater efforts to find suitable employees and jobs, respectively. Based on economic theory, labour market tightness is either a function of the job vacancies to aggregate job search (Landais et al., 2018a; Pei and Xie, 2020) or the ratio of job vacancies to unemployment (e.g. Pissarides, 1985; Petrosky-Nadeau and Wasmer, 2013). Job searches can also be used to observe the moral hazards of unemployment insurance (Lachowska et al., 2016; Landais et al. 2018a, 2018b; Kuka, 2018) and measure the impact and effectiveness of unemployment insurance policies. Given the importance of job search and labour demand in the labour market, this study estimates the effect of FPU on these two important labour market variables.

We first consider that FPU affects many countries and can be observed in different ways. In countries where public finance is unsustainable, households and firms potentially expect frequent changes in future tax rates and/or expenditure programmes, though they may be uncertain about the timing of these changes. In countries where public finances are relatively sustainable, their FPU may increase significantly due to political polarisation and changes in government (Roubini and Sachs, 1989; Perotti and Kontopoulos, 2002). Second, the detrimental effect of FPU on the economy remains debatable. Although Fernández-Villaverde et al. (2015) observe a negative effect of FPU on the economy, Born and Pfeifer (2014) argue that the pure uncertainty (separated from shock realisations) effect of monetary and fiscal policy is unlikely to play a major role in business cycle fluctuations. Bi et al. (2013) instead suggest that, depending on other economic factors such as the monetary policy stance or the level of government debt, FPU could generate positive or negative effects on the economy.

This study makes several contributions to the literature. First, to the best of our knowledge, the effect of FPU on US job search behaviour and labour demand has not been estimated before. To this end, we propose a language-independent approach, which enables us to construct new measures that incorporating job search behaviours across both native and other language job seekers. This method is applied to US data in this study, but it could also be applied to data from other countries.

Second, we contribute to the growing literature on the economic effects of uncertainty (Pástor and Veronesi, 2013; Handley and Limao, 2015; Baker et al., 2016; Gulen and Ion, 2016; Leduc and Liu, 2016). In particular, Caggiano et al. (2014), Leduc and Liu (2016), and Schaal (2017) estimate the effect of uncertainty on the macro labour market, while mainly focussing on unemployment (labour supply). We build on this research and provide evidence that FPU decreases both job searches and job postings (labour demand). Moreover, we differentiate the effect of uncertainty from that of risk and consider the endogeneity problem. FPU is also found to affect labour market matching efficiency.

Third, our study also contributes to the literature concerning the determinants of job searches or labour demand. Previous studies have illustrated that job satisfaction (Delfgaauw, 2007), economic conditions (Mukoyama et al., 2018; Pan, 2019), individual characteristics (DellaVigna and Paserman, 2005), search methods (Addison and Portugal, 2002; Kuhn and Mansour, 2014), unemployment benefits (Krueger and Mueller, 2010; Marinescu, 2017), and networks (Cingano and Rosolia, 2012) are among the determining factors of job searches. Labour cost and labour productivity (Bentolila and Bertola, 1990; Pfann and Palm, 1993) as well as employment protection (Nunziata, 2003) are found to affect firms' labour demand. Although past studies have improved our understanding of job search (postings) behaviour, they do not explore the influence of FPU. Therefore, we examine FPU as a determining factor in job search behaviour and labour demand.

Fourth, our study is related to the growing literature stream that uses online job portal data or studies online job search behaviour. For instance, Kuhn and Mansour (2014) analyse data from the US National Longitudinal Survey of Youth and conclude that, among the unemployed, those who searched for jobs online were re-employed on average 25% faster than similar workers who did not search for jobs online. Using data from a leading employment board, CareerBuilder.com, Marinescu and Rathelot (2018) analyse how geography affects job searches and conclude that job seekers are less likely to apply for jobs in a distant location. Using the same dataset, Marinescu and Wolthoff (2020) find that job titles explain nearly 90% of the variance in explicit wages.

The remainder of this paper is structured as follows. Section 2 describes the data sources and the basic descriptive statistics of key variables. Section 3 reports the empirical strategy for analysing the effect of FPU on the labour market. Section 4 presents the main empirical findings. Section 5 explains the robustness checks conducted to support our main findings. Section 6 presents the conclusions.

2 Data

2.1 Job board data

We use data collected by Burning Glass Technologies (BGT), a private sector firm that scrapes more than 40,000 online job boards daily, resulting in a dataset capturing the quasi-universe of all online job ads (Hershbein and Kahn 2018), with a total over 150 million US job postings over the period January 2010 to April 2018. Kuhn et al. (2018) and Hershbein and Kahn (2018) compared this dataset with the JOLTS dataset, which is another source for job postings and conclude that the industry composition of the JOLTS vacancies was similar to that of BGT data, but BGT data contained more detailed information and had a higher frequency. Another advantage of this dataset is that it does not rely on a single job board such as CareerBuilder.com.

Figure 1 displays the monthly average number of job postings for each state. Note that our sample period begins from February 2010 since January 2010 data are missing for many states. Since a few days data are missing, we consider a simple daily average rather than summing up the daily figures to obtain monthly number of job postings. Clearly, the job postings trends vary across states. For example, there was a spike in 2013 in many states including West Virginia and Utah, but we do not observe this spike in Nevada and Kentucky. However, we can observe an obvious upward trend during the sample period. This is expected as online job postings have become more popular over the years (see Kuhn, 2014; Kuhn and Mansour, 2014).

Since we have daily job postings data, it would be insightful to analyse whether there is weekday or weekend effect of labour demand. This enables us to document the property of firm's labour demand. The Panel A of Figure 2 reports the average postings across states for each weekday. It can be easily observed that the number of job postings is lower during weekends. During weekdays, the number gradually increases from Monday and typically peaks on Friday, which is in contrast to the case of job search found in Baker and Fradkin (2017), who find that job search activity generally peaks in the earlier part of the work week.

Based on Figure 1, the number of job posting appears to demonstrate seasonality. Moreover, other labour market variables, such as unemployment and hiring rate, have seasonal behaviour. Thus, it is natural to check whether job postings exhibit seasonality. Panel B of Figure 2 reports the number of job postings averaged across states for each month. It shows that job posting numbers peak in March and June, and register the lowest numbers in December, similar to job search activity. This suggests that firms are typically less likely to adjust their employee structures at the end of year.

2.2 Aggregate job search

To measure country-level job search, we mainly follow Baker and Fradkin (2017) and use the search volumes of particular keywords as a proxy for job search behaviour. The assumption is that job seekers use specific keywords in their job search. This approach is adopted because it is based on and can track millions of Internet users at any point in time, thus negating the need to conduct a survey, which might suffer from sample bias.[3] Moreover, Stephens-Davidowitz (2014, 2017) and Da et al. (2015) advocate the use of internet search data over survey data given that the survey respondents have a low incentive to provide honest responses, leading to potentially biased survey results.

Baker and Fradkin (2017) provide supportive evidence that these online job search indices can be representative of overall job search behaviours. They review several survey results, including those from the National Longitudinal Survey of Youth and the 2011 Internet and Computer Use supplement of the Current Population Survey, and conclud that more than two thirds of the respondents had searched for work online. Their study have one other major concern—whether Google searches could function as a good proxy for overall online job searches. Baker and Fradkin (2017) compare their indices with individual browsing data from comScore and show that their indices are highly analogous to time spent visiting job search websites.

[3] As shown by Baker and Fradkin (2017), the most commonly used data source in the United States to estimate job search behaviours is the American Time Use Survey (ATUS). However, ATUS survey data often contain fewer than five unemployed respondents per state-month.

However, we extend Baker and Fradkin's (2017) approach. The authors use the term 'jobs' as the primary search keyword. As shown by these authors, this term effectively reflects the aggregate online job search activities. However, the use of 'jobs' as the primary keyword perhaps captures the job search activity of English-speaking job seekers, while ignoring other language job seekers within a country. For example, Spanish is the second most common language in the United States; hence, only looking at 'jobs' may ignore Hispanic job seekers.

In this study, we propose to leverage the Google Trends feature that enables analysis of search topics rather than being restricted to select search terms. Search terms show matches for all terms in the query, in the given language, while search topics are a group of terms that share the same conceptual meaning in any language. For example, if we search for 'London' the search volume includes results for topics such as 'Londres' ('London' in Spanish).[4] Thus, this allows us to construct language-independent job search indices and develop an aggregate job search index that incorporates non-native language job seekers within a country. Figure 3 compares our index and Baker and Fradkin's (2017) index at national level. It is clear that our index systematically higher than that of Baker and Fradkin's (2017) one. This meets our expectation because our index covers all language job seekers in the United States.

We use the search topic of 'job' as a proxy for aggregate job search behaviour. Our sample data starts from February 2010, and ends in April 2018 because of BGT data availability. Figure 4 plots the job search indices across 50 U.S. states and the District of Columbia[5] and shows that the job search indices vary across regions, even though we see some similarity in patterns for certain periods. For example, we observe that job search indices in most states decreased during

[4] Please refer to Google Trends for more information https://support.google.com/trends/answer/4359550?hl=en.

[5] For convenience, we use the term 'state' to refer to the 50 U.S. states and the District of Columbia that are included in this study.

the period of 2010 to 2014. However, such a decrease does not appear in Oregon, Vermont, and Virginia. Although most states' job search levels roughly maintained at similar after 2014, some states such as Idaho, Montana, South Carolina, Utah, and Wisconsin, continued to show a further decrease in the level of job search activity.

As can be observed, Figure 4 seems to demonstrate seasonality in job search.[6] To check whether job search indeed exhibits seasonality, Figure 5 reports the job search index averaged across states for each month. Taking a closer look, we observe that job searches peak in January and June, with the lowest activity levels registered in December. This is intuitive because individuals may wait to receive their year-end bonus before searching for a new job.

2.3 Fiscal policy uncertainty index

Baker et al. (2016) use a text-searching technique for newspaper articles and define the proportion of policy uncertainty-related articles to the total number of articles as the policy uncertainty index.[7] They first searched for articles containing the term 'uncertainty' or 'uncertain', 'economic' or 'economy', and one or more of the following terms: 'congress', 'legislation', 'white house', 'regulation', 'federal reserve', or 'deficit' in ten leading national newspapers (namely USA Today, The Miami Herald, The Chicago Tribune, The Washington Post, The Los Angeles Times, The Boston Globe, The San Francisco Chronicle, The Dallas Morning News, The Houston Chronicle, and The Wall Street Journal) from January 1985 to April 2020 to generate the policy uncertainty index. Aside from the aggregate economic policy uncertainty index, the authors also

[6] We do not report the weekday and weekend effects on job search as our results are similar to that of Baker and Fradkin (2017).
[7] Bloom (2014) review common approaches on measuring uncertainty.

provide several sub-indices, including the FPU index, by using additional sets of terms. Instead of the above three main sets of terms, they applied one additional term set that is related to taxes or government spending, and counted the number of FPU-related articles that contained one or more of these terms.[8] The authors then computed the ratio between the raw count of FPU-related articles to total articles for each newspaper. To handle the issue of changes over time in the volume of articles for each newspaper, they normalised the resulting series. Finally, they aggregated the normalised values over papers for a given month to obtain a multi-paper index. The multi-paper index is re-normalised to an average value of 100 from January 1985 through December 2009.

Another question about the policy uncertainty index is whether newspaper articles are a reliable source of information because their reporting may be biased. For instance, right-leaning newspapers may tend to emphasise policy uncertainty when the Republican Party are in power, and vice versa. To address this concern, Baker et al. (2016) use the Gentzkow and Shapiro (2010) media slant index to split the ten leading national newspapers into the five most left-leaning and the five most right-leaning ones. They separately calculate the policy uncertainty index for each of these two sets of newspapers and observe that the resulting policy uncertainty index is highly correlated. Furthermore, the authors calculate the proportion of 'uncertain' or 'uncertainty' in the Beige Books released before Federal Open Market Committee meetings. The uncertainty index based on the Beige Books is highly correlated (over 80%) with the benchmark economic policy uncertainty index. These two robustness checks support the view that newspaper articles do not contain significant biases in reporting policy uncertainty.

Figure 6 shows the time-series plot of the FPU index from January 2010 to April 2018. The sample date range corresponds with labour market data availability. It is noticeable that the

[8] The actual terms used to develop the FPU index can be found at http://www.policyuncertainty.com/categorical_terms.html.

FPU spikes correspond to several policy events. For example, the spike in August 2011 relates to the enactment of Budget Control Act. Each of the fiscal cliff in 2012, government shutdown in 2013, and more recently, as well as Trump's 2017 tax cut reform sparked a spike in FPU.

3 Empirical approach

The baseline empirical model is specified as follows:

$$\mathrm{Y}_{i,t} = \alpha + \varphi_i + \beta_1 FPU_t + \beta_2 X_{i,t} + \mathrm{Month}_t + \mathrm{Trend}_t + \varepsilon_{i,t}, \qquad (1)$$

where i denotes the state; t denotes the time; $Y_{i,t}$ is the job search index or number of job postings for state i at time t; FPU_t is the logarithm of the FPU index, as developed by Baker et al. (2016), β_1 is the primary variable of interest; Month_t is the month dummy variable meant to control for possible seasonality in job search and job posting activity; and φ_i is the state fixed effect, capturing state-specific differences. The time trend variable, Trend_t, captures the possible time trend in online job search activity or postings. This is important since the number of job seekers or firms using the internet to search and advertise jobs is increasing (Kuhn and Skuterud, 2004; Stevenson, 2008; Kuhn and Mansour, 2014). $X_{i,t}$ is a set of controls, including the state unemployment rate, squared term of the unemployment rate, and labour force participation.[9] These factors reflect the general labour market conditions and local economic environments, and are shown to affect job search (e.g. Baker and Fradkin, 2017) as well as job postings. In particular, controlling for unemployment is important in explaining labour demand as unemployment has a

[9] The unemployment and labour force data are collected from the US Bureau of Labor Statistics.

strong negative relationship with job vacancies as per the standard search-matching theory (see Pissarides, 1985; Mortensen and Pissarides 1994).[10] Following Petersen (2009), standard errors are clustered by month and state to control for potential cross-sectional and serial correlation in the error term.

We expect that FPU reduces labour demand and is reflected in lower numbers of job postings. Based on the real option theory, a firm's value of waiting increases during uncertain times, leading them to postpone finance and investment decisions (see, for example, Bernanke 1983; Abel and Eberly, 1996; Bloom, 2009). Thus, we expect that firms would reduce the number of job posts during rising FPU. Regarding the effect of FPU on job search intensity, its effect may also be negative. The standard search and matching models suggest job search effort should be procyclical. Gomme and Lkhagvasuren (2015) also find that empirical job search is procyclical. Given the fact that policy uncertainty is countercyclical (Bloom, 2014), we should expect FPU has negative effect of job search.[11]

One potential challenge faced in our study pertains to omitted variables. If these unobservable variables remain stable over time, we can use state fixed effects to control for them. We also add more control variables to further reduce this concern through our robustness checks. The second challenge faced in our study is identifying FPU's causal effect on policy uncertainty without initiating reverse causality. In Section 5, we provide additional robustness checks, including testing for endogeneity, to mitigate concerns of reverse causality.

[10] Empirically, a graphical representation of the relationship between unemployment and the job vacancy rate is called a Beveridge curve. This curve helps to investigate the matching efficiency in the labour market. Please see Elsby et al. (2015) for a review of literature on this topic.
[11] Note that in some studies (e.g. Shimer, 2004; Mukoyama et al., 2018; Pan, 2019), they show that empirical job search effort may be countercyclical.

4 Main results

This section focuses on the effect of FPU on job searches and labour demand. We provide several additional analyses to show how the effects of FPU vary under different conditions.

4.1 Baseline results

Table 1 reports the estimation results of our baseline regression model. Columns (1) to (5) display the results for labour demand. Column (1) reports the effect of FPU on the number of job postings without any controls and fixed effects. We find that FPU reduces the number of job postings at the 1% significance level. The estimated coefficient of FPU is -0.284 (t-statistic is about -10), which suggests that if FPU increased by 100%, the number of job postings would be reduced by 28.4%. This economic magnitude is important as the logarithm of the FPU index has an average of 0.588 standard deviations, indicating that it commonly changes by more than 50%. This magnitude is particularly important considering that the FPU index more than doubled within a year during well-known, recent events, such as the 2013 government shutdown. When the state fixed effect, time trend and monthly dummy variables (columns (2) to (4), respectively) are included in the model, the impact of FPU remains negative and significant at the 1% level. The last column shows the outcomes when we control for state unemployment rate and labour force participation. We observe that the coefficient of FPU remains significantly negative at the 1% level, with a magnitude of -0.098, showing that a 1% increase in FPU leads to a 0.098% decrease in labour demand. This result meets our expectation that firms tend to reduce or delay their labour demand when the uncertainty is high.

Columns (6) to (10) of Table 1 report the FPU effect on job searches. We find that FPU increases the job search level at the 1% significance level. The FPU coefficient is -0.022 (t-statistic=7.33), which suggests that if FPU increases by 100%, the job search index would decrease by 2.2%. When the state fixed effect is included in the model (column (2)), the FPU effect remains negative and significant at the 1% level. This finding is robust after including month dummies and the linear time trend of job search activity. For example, the FPU coefficient in column (4) is -0.015 with a t-statistic of around -5 (-0.015/0.0003). Lastly, we include the unemployment rate and labour force participation into the equation and observe that the FPU effect on job searches is significantly negative with a coefficient equal to -0.021 and a t-statistic that exceeds 7. This result is consistent with the prediction from standard search and matching models, implying that during the bad times, the return on search effort is lower, leading to lower job search effort.

4.2 Subsample analysis

Geographical differences

Another perspective is the effect of FPU on job search behaviour, when considering geographical variations. As noted by Blanchard and Katz (1992), various states experience different shocks to labour demand because they produce different bundles of goods. Instead of looking at all US states together, we classify our sample into four census regions based on four geographical locations: Northeast, Midwest, South, and West.[12] This investigation provides policymakers and researchers with insight on the extent of the difference in the FPU effect being experienced by different regions. Table 2 summarises the average pairwise correlation of the job

[12] This classification follows the US Census Bureau (https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf). The Appendix lists the classifications.

search index and number of job postings. Overall, both job search activity and job postings are highly correlated, with an average correlation of over 54% among all states. In addition, job search and job postings are significantly more synchronised in the Midwest region, with an average correlation of around 80%. States within the West and Northeast regions show the lowest level of synchronisation.

Table 3 shows that FPU has a significantly negative effect on job postings but with differing economic magnitudes across the regions and that there is a stronger effect in the Midwest region, regardless of the economic or statistical magnitude. Furthermore, the result indicates that a 1% increase in FPU leads to a 0.126% decrease in job postings in that region. For a 1% increase in FPU, job postings decrease by less than 0.1% in the other three regions.

Regarding the effect of FPU on job searches, the results are similar. They indicate that the South region is more sensitive to FPU shocks, compared to the other three regions. For a 1% increase in FPU, job search decrease by more than 0.03% for this region. The results also indicate that both the Northeast and Midwest regions experience significant drop in job search activity due to FPU. Only job search in the West region do not significantly in response to rising FPU.

The role of institutional factors

Thus far, we have not considered the role of institutional factors in driving the effect of policy uncertainty on job searches. Blanchard and Wolfers (2000) argue that adverse shocks are insufficient to explain cross-country differences in European labour markets and emphasise the role of labour market institutions. Furthermore, it is possible that institutional factors are not only important in explaining cross-country differences but also in explaining regional disparities within a country. For example, Leduc and Liu (2016) and Mumtaz et al. (2018) show that heterogeneity in labour market rigidity can determine the magnitude of the effect of uncertainty on the local labour market.[13] In a more rigid region, the effect of uncertainty may be amplified.

To examine how institutions affect the mechanism through which FPU affects the labour market, we interact the FPU index with the Fraser Institute union density and minimum wage law ratings, as follows.

$$Y_{j,t} = \beta_0 + \beta_1 FPU_t + \beta_2 Insti_{j,t} + \beta_3 FPU_t \cdot Insti_{j,t} + \gamma_1 X_{j,t} + u_j + \varepsilon_{j,t}, \qquad (2)$$

where $Insti_{j,t}$ refers to institutional factors. The higher rating of these indices shows more economic freedom in labour markets (i.e. less rigidity). The basic concept is that a state with stronger employment protection is likely to be more significantly affected by FPU. Table 4 reports the estimation results.

The coefficients of interaction terms are the main point of interest. The interaction term between union rating and FPU is significantly positive in the case of labour demand. This shows that for states that are less affected by unions, the decrease in the number of job postings due to the FPU is less significant. The interaction term between minimum wage legislation rating and FPU is also positive, but insignificant. These findings are consistent with the view that states with more economic freedom tend to mitigate the effect of FPU on job postings. This is reflected in the smaller decrease in job posting activity experienced by states that are less affected by legislation or unions during times of rising FPU.

[13] Montgomery (1993) estimates the pattern of local labour markets in the US and Japan and concludes that local differences in institutions do exist. Specific examples include differences in unemployment insurance programs and minimum wage laws.

We also investigate the role of institutional factors on the FPU-job search relationship. The results reported in Table 4 (columns (3) and (4)) again support the view that more flexibility helps to reduce the negative effect of FPU on labour markets. For example, states with higher economic freedom scores experience a less significant decline in the number of job postings in response to rising FPU. The results in Table 4 offer a possible explanation of why FPU has different effects on labour markets across regions. Institutional factors, especially unions, may provide one possible explanation of these differences.

The monetary policy stance

As documented by the literature, one important condition in understanding the effect of FPU is the monetary policy stance. Bi et al. (2013) suggest that FPU could generate positive or negative effects on the economy, depending on the monetary policy stance. Johannsen (2014) further argues that FPU causes large negative effects on investment, consumption, and output in the time of zero lower bounds (ZLB).[14]

In accordance with these findings, we divide our sample into two, based on periods where the effective federal funds rate was lower than 0.25% and greater than 0.25%.[15] The results listed in Table 5 support the view that the effect of FPU on the labour market is conditional on the monetary policy stance. The results suggest that FPU has a greater impact on labour demand during non-ZLB periods. A 1% increase in FPU leads to around a 0.15% decrease in number of job postings, which is much greater than that of the ZLB period (0.026%).

[14] The ZLB rate refers to the time that interest rates have fallen as far as they can. Please see https://www.economicshelp.org/blog/7603/economics/zero-lower-bound-rate-zlb/ for brief introduction of ZLB.
[15] The data are collected from the Federal Reserve Economic Data database.

Similarly, our results indicate that FPU has a stronger effect on job search in non-ZLB period. One reason for this phenomenon could be that job seekers face too much uncertainty. The model and experiment results from Falk et al. (2006) demonstrate that when job seekers exhibit substantial uncertainty about their job-finding prospects, they are likely to stop searching and enter a state of nonparticipation in the labour market. This leads to a decrease in the job search volume. The interest rate policy associated with ZLB was used to help the economy recover from the 2007-09 crisis. This implies that individuals face financial uncertainty during a ZLB period. Another reason for the contrary effects is that the return on searching for any given worker is arguably lower during bad times, and search effort declines when return on searching is lower. The results of the negative effect of FPU on job search during ZLB periods are also consistent with the results of Potter (2020), who finds that job search declines monotonically during the 2007-09 financial crisis.

The role of debt level

The effect of FPU on an economy may depend on level of federal debt and household debt. Aside from monetary policy stance, Bi et al. (2013) suggest that FPU's effect also depends on the level of government debt. Bi et al. (2016) provide empirical evidence to support this view and further point out that the wealth effect on labour supply is key to explain it. In accordance with these findings, we divide our sample into two, based on periods where the ratio of federal debt to GDP was lower than 100% and greater than 100%.

The results reported in Table 6 suggest that FPU has a significantly negative impact on labour demand during the level of high federal debt. A 1% increase in FPU leads to around a 0.101% decrease in number of job postings, which is much stronger than that of the low debt period (decrease by 0.036%). Similarly, our results indicate that FPU has a stronger effect on job search in high debt period. It suggests 1% increase in FPU lead to 0.031% decrease in job search. During the low level of federal debt, the FPU has insignificant impact on job search. In sum, our results show that the magnitude of FPU's effect on labour market depends on the level of government debt.

Tax versus government spending uncertainty

Thus far, our results document the strong effect of FPU on the labour market. One important feature which has not yet been considered is isolating the effect of government spending and tax, which are two main fiscal policy components. Baker et al. (2016) offer an index for tax policy uncertainty and government spending uncertainty. We separately replace our FPU index with these two sub-indices and re-run the investigation. The regression results summarised in Table 7 show that both job seekers and the firm's labour demand are more sensitive to tax policy uncertainty. However, both tax policy and government spending uncertainty have a significant impact on these two variables.

The persistence of the FPU effect

The effect of FPU on labour markets might persist over time as uncertainty has lagged effects on firm decisions, such as capital investment and employment. Bloom (2009) finds that hiring and investment rates drop dramatically four months after an uncertainty shock because higher uncertainty increases the real-option value of waiting for a rebound in approximately six months. We respectively run the baseline regression using the future value of the job search index and job postings for up to six months as the dependent variables. We then plot the coefficients of FPU in Figure 7, with the corresponding 95% confidence intervals.[16]

Labour demand initially drops at time *t*, with the largest drop at *t+1*. This indicates that as firms need time to make decisions to postpone their labour demand, FPU has the greatest effect on labour demand at time *t+1* instead of *t*. Then, the negative effect of FPU on job postings gradually disappears. This finding is remarkably similar to Bloom's (2009) finding that increased uncertainty causes a drop and a rebound after the largest effect. Similarly, job search activity decreases initially, at time *t*, in response to rising FPU. The negative effect of FPU on job search peaks at time *t+1*, and gradually become weaker.

4.3 Matching efficiency and fiscal policy uncertainty

This study adopts three important variables (i.e. unemployment, job vacancies, and job searches) that enable tests of whether FPU affects matching efficiency to be conducted. For this, the following two regression models are developed, following Wall and Zoega (2002) and Nickell et al. (2003):

$$U_{j,t} = \beta_0 + \beta_1 FPU_t + \beta_2 V_{j,t} + job\ search_{j,t} + u_j + \varepsilon_{j,t}, \quad (3)$$

$$VU_{j,t} = \beta_0 + \beta_1 FPU_t + job\ search_{j,t} + u_j + \varepsilon_{j,t}, \quad (4)$$

[16] Note that control variables also change with the dependent variable. For example, if the dependent variable is at *t+1*, the controls are also recorded for the *t+1* period.

The first model assesses whether the coefficients of job postings ($V_{j,t}$) are different before and after adding the FPU index, while the second one assesses whether FPU affects the job postings-unemployment ratio (labour market tightness, $VU_{j,t}$).[17] Note that the log of unemployment numbers is applied, rather than the unemployment rate, because data was only available for the number of job postings and not the job postings rate or job vacancies rate. The coefficient of FPU in equation (3) can be interpreted as the elasticity of the labour market. Comparing columns (1) and (3) of Table 8, we observe that the coefficient of job postings becomes less negative when FPU is included. This indicates that the labour market become less efficient. For robustness, we add the job search indices that we developed in this study because job search effort is a key factor driving matching efficiency. We still observe that the labour market becomes less efficient (comparing columns (2) and (4)). In the last two columns, we show that FPU decreases labour market tightness, which again supports the view that FPU reduces matching efficiency in the labour market (see columns (5) and (6)).

5 Robustness checks

In this subsection, we present a battery of robustness checks, considering endogeneity concerns, isolating the effect of uncertainty from risk, considering, omitted variables and extreme outliers, investigating the effects of Google's market share and increasing Internet usage, and analysing different clustering methods for standard errors.[18]

[17] We realise that some studies define the matching function as the ratio of aggregate search to unemployment (e.g Landais et al., 2018; Pei and Xie, 2020). We use this alternative setting for additional checks and results are qualitatively the same.
[18] We note that forecasting disagreement is another approach to measure FPU. We also test whether forecasters' disagreements about US federal government consumption, a proxy for FPU which is based on the Philadelphia Fed's

Endogeneity concerns

Our first issue concentrates on endogeneity problems. First, the FPU measure used in this study might capture economic uncertainty that is not policy related but, at the same time, affects job searches or labour demand. Canada and the United States are linked by extensive trade relations such as the Canada-United States Free Trade Agreement (CUSFTA) and the North American Free Trade Agreement (NAFTA). Based on IMF (2005) and the US Department of State, the relationship between the United States and Canada has been the largest bilateral trading relationship in the world, and Canada remained the United States' second-largest trading partner in 2019.[19] Hence, their economic uncertainties should be highly correlated. We follow Gulen and Ion (2016) to regress the US FPU on the Canadian economic policy uncertainty (EPU) using the following model:

$$FPU_t = \alpha + \beta \cdot Canadian\ EPU_t + \varepsilon_t, \tag{5}$$

where the residual of the above regression (ε_t) captures the FPU that is orthogonal to the Canadian EPU. This residual is used to replace the FPU in equation (1). Panel A of Table 9 show a significant and negative relation between FPU, proxy by the residual, and job searches (postings) at the 1% significance level.

Second, we use Azzimonti's (2018) partisan conflict index (PCI) as an instrument for FPU.[20] The PCI is clearly positively related to the FPU index as higher PCI levels reflect more

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Survey of Professional Forecasters (SPF) can affect the labour market. Our results are qualitatively the same and are available upon request.

[19] https://www.state.gov/u-s-relations-with-canada/

[20] The PCI data is available at the Philadelphia Fed's website at https://www.philadelphiafed.org/research-and-data/real-time-center/partisan-conflict-index.

disagreement among political parties, the Congress, and the President, and thus, a higher level of policy uncertainty. Nevertheless, the individual job search decision is less likely to directly correlate to partisan conflict. We use the following regression to perform the first-stage estimation where $X_{i,t}$ refers to all the control variables used in the baseline regression:

$$FPU_t = \alpha + \beta \cdot PCI_t + \gamma \cdot X_{i,t} + \varepsilon_t. \quad (6)$$

As shown in the first column of Panel B of Table 9, a significant and positive PCI coefficient suggests that a higher partisan conflict is indeed significantly associated with a higher FPU. In the second stage (columns (2) and (3)), the fitted FPU variable has a significantly negative effect on both job search and job postings, which is significant at the 1% level. Overall, based on the above two analyses, the positive FPU effect on job searches and labour demand is not tainted by potential endogeneity.

Risk versus uncertainty

It is important to disentangle the effect of uncertainty on labour markets from risk. Particularly, Berger et al. (2020) argue that the negative effect of uncertainty on the economy found in the literature is driven by the realisation of volatility, rather than uncertainty. The authors use implied volatility and realised volatility of the S&P 500 index as a proxy for risk and uncertainty, and show that shocks to forward-looking uncertainty have no significant effect on the economy when the model includes realised volatility (risk). In this study, we follow Berger et al. (2020) and use the sum of daily squared stock returns during month *t*.

Table 10 provides the estimation results after including realised volatility. The FPU coefficient in columns (1) and (3) is significantly negative. This indicates that when we disentangle

FPU from risk (even partially), the result still shows that FPU decrease both job searches and labour demand.

Another approach we employ to disentangle the FPU's effect from policy risk is to add an alternative policy-induced risk measure. Baker et al. (2019) create a newspaper-based Equity Market Volatility (EMV) tracker that moves with the CBOE Volatility Index (VIX). The authors particularly develop a fiscal policy-related EMV measure, which isolates the economic news' effect on driving this fiscal policy-related EMV index. We add this index into our baseline regression and re-estimate it. The result still supports the view that FPU significantly decreases aggregate job searches and labour demand (see columns (2) and (4) in Table 10).

Regarding the effect of risk on job searches, increasing realised equity volatility increases job searches and job postings. However, this positive risk effect is only observed for one month at a time in scenarios where the previous-month risk has no significant effect on both variables. The FPU-related risk measure also do not have significant on both variables.

Controlling for other uncertainties

One can probably argue that uncertainties other than FPU affect labour markets. We, therefore, separately add macroeconomic, financial (Jurado et al., 2015), and geopolitical (Caldara and Iacoviello, 2018) uncertainty indices into the baseline regression.[21] Table 11 shows the estimated results. Overall, the FPU effect on job search and labour demand remains significantly negative at the 1% level. These findings show that the observed effects are not confounded by other types of uncertainties. Other types of uncertainty also decrease these two variables. One

[21] The macroeconomic and financial uncertainty indices are econometric estimates based on various economic activity variables. Jurado et al. (2015) provide one-month, three-month and 12-month ahead indices. We use the one-month ahead index. We also test using six-month and 12-month indices and find that the qualitative conclusions do not change.

interesting observation is FU increase the job searches. This may be the result from wealth effect suggested by Mukoyama et al. (2018). The authors argue that job search increase during the 2007-2009 financial crisis because of the huge decline in asset markets, leading job seekers have more losses of wealth and put greater job search effort.

Extreme Outliers

Next, we address the issue of outliers because we observe that FPU sharply increases for certain months. This, in turn, increases the concern that our results are driven by outliers. To mitigate this concern, we winsorise all variables at the 1% and 5% levels and use the 1% and 5% winsorised variables to re-estimate the baseline regressions. The results summarised in Panel A of Table 12 show that the negative relationship between job search (or job postings) and FPU remains significant at the 1% level.

Google market share and increasing Internet usage

One can probably argue that the increasing number of Google users or Internet users may lead to increasing search volumes, which may bias our estimation results. To address this concern, we regress the cyclical component of job searches (postings) on the FPU index. We primarily employ the de-trending method proposed by Hamilton (2018), which uses a cycle length of two years for monthly observations (i.e. h=24 months).[22] The regression results for the cyclical component and FPU is summarised in Panel B. Overall, our results remain robust, also implying that FPU can explain the cyclical behaviour of job searches and job postings.

[22] The Hamilton approach involves conducting an ordinary least squares (OLS) regression of the variable at date $t + h$ on the four most recent values on date t to avoid these drawbacks and to obtain a cyclical component series. The residual is a cyclical component of the variable. This approach overcomes the problems of the Hodrick–Prescott filter, which produces a series with spurious dynamic relationships and no basis in the underlying data-generating process.

Clustering standard errors by state or time only

In our main results, we use two-way clustering (by state and month) for standard errors. It is arguable whether our approach is sufficiently conservative. In particular, if FPU does not vary by state, this could increase standard errors substantially given the serial correlation in FPU. To reduce this concern, we respectively re-estimate the baseline model by using different clustering methods. The results reported in the Panel C of Table 12 remain robust.

6 Conclusion

In this study, we investigated whether FPU affects job searches and job postings in the US by creating a new set of job search indices for all 50 states and the District of Columbia. We found that FPU has a negative effect on both job searches and job postings, with different regions responding differently. Our results reveal that institutional factors are key to explain the different effects of FPU on regional labour markets, as we observed that states with more economic freedom area experience less of an impact of FPU on their labour markets. FPU's negative effect on job searches and postings are subjected to the monetary policy stance and the level of government debt. Lastly, FPU also reduces matching efficiency in local labour markets.

Our preliminary analysis provides evidence of a negative relationship between job searches (job postings) and policy uncertainty. These results offer implications for researchers and policymakers. First, it is important for search and matching models to explicitly incorporate policy uncertainty into models. Second, reducing labour market rigidities can help to mitigate the negative effect of FPU on the labour market. Third, it is important to consider the debt level and monetary policy when evaluating the effect of fiscal policy on the economy.

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Appendix A

The list of region classification:

Northeast Region: Maine, New Hampshire, Vermont, Massachusetts, Rhode Island, Connecticut, New York, New Jersey, Pennsylvania

Midwest Region: Ohio, Indiana, Illinois, Michigan, Wisconsin, Minnesota, Iowa, Missouri, North Dakota, South Dakota, Nebraska, Kansas

South Region: Delaware, Maryland, District of Columbia, Virginia, West Virginia, North Carolina, South Carolina, Georgia, Florida, Kentucky, Tennessee, Alabama, Mississippi, Arkansas, Louisiana, Oklahoma, Texas

West Region: Montana, Idaho, Wyoming, Colorado, New Mexico, Arizona, Utah, Nevada, Washington, Oregon, California, Alaska, Hawaii

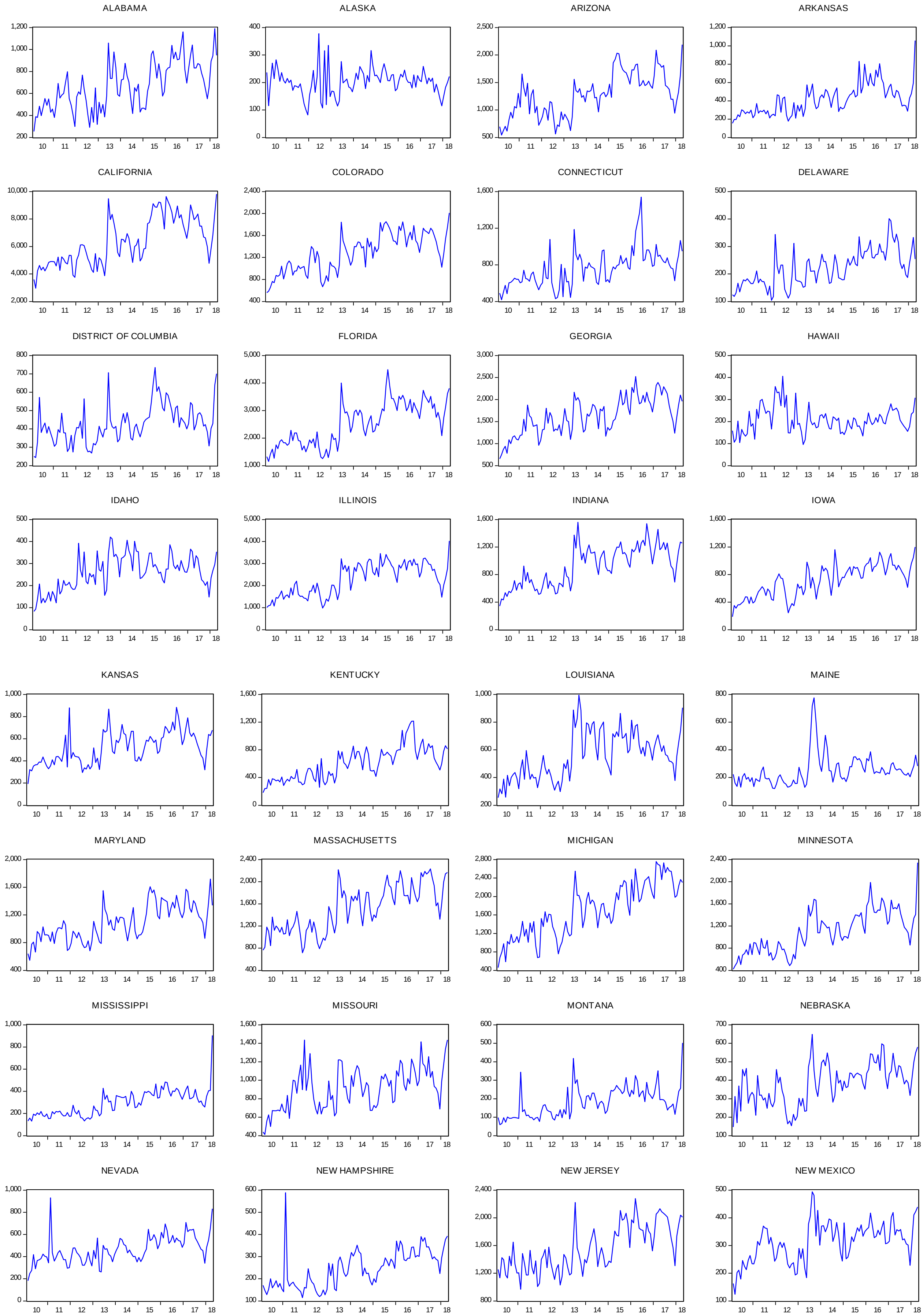


Figure 1: Number of Job postings across states

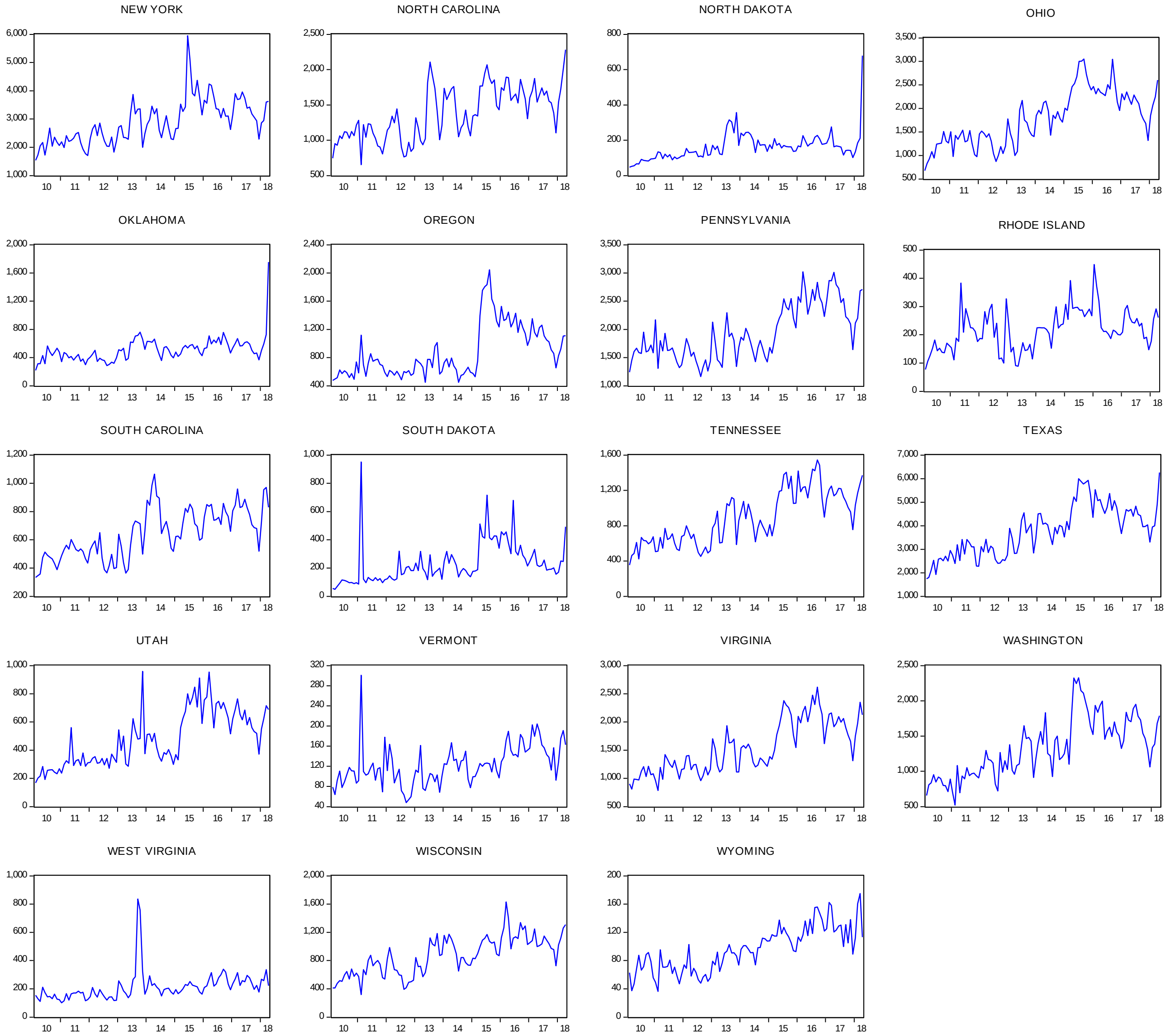
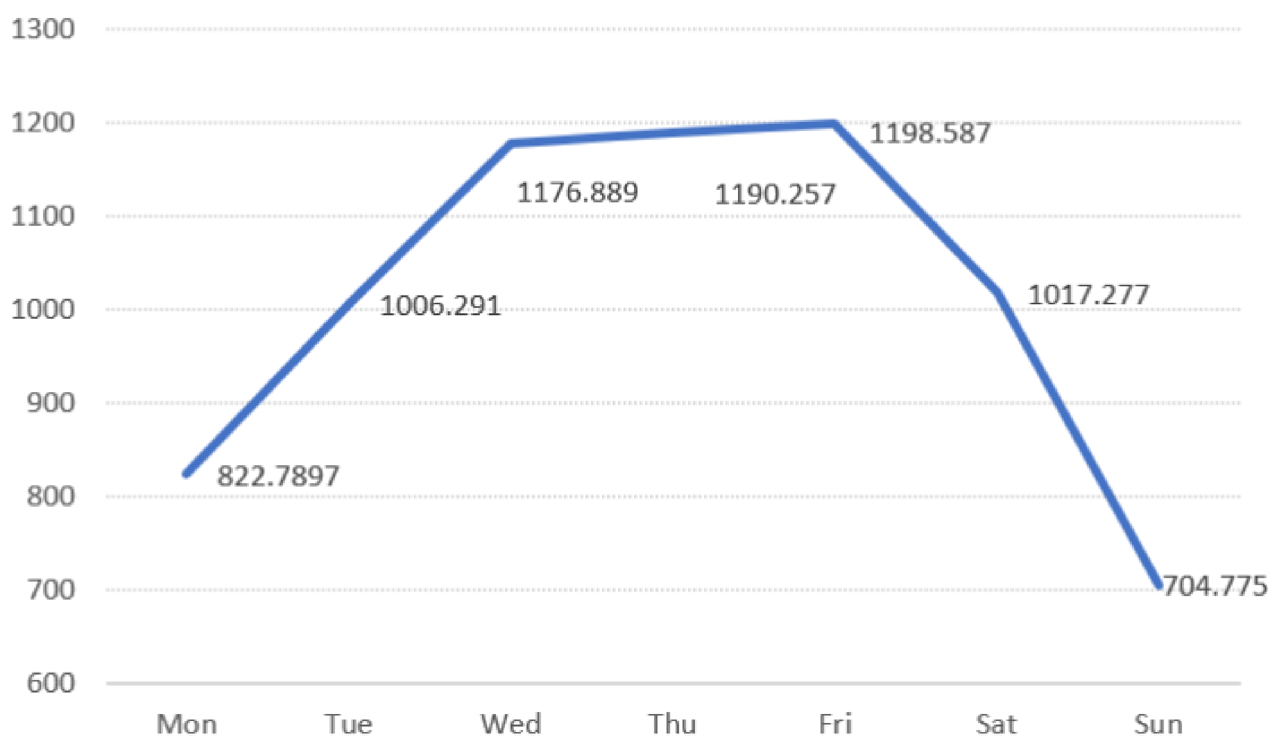
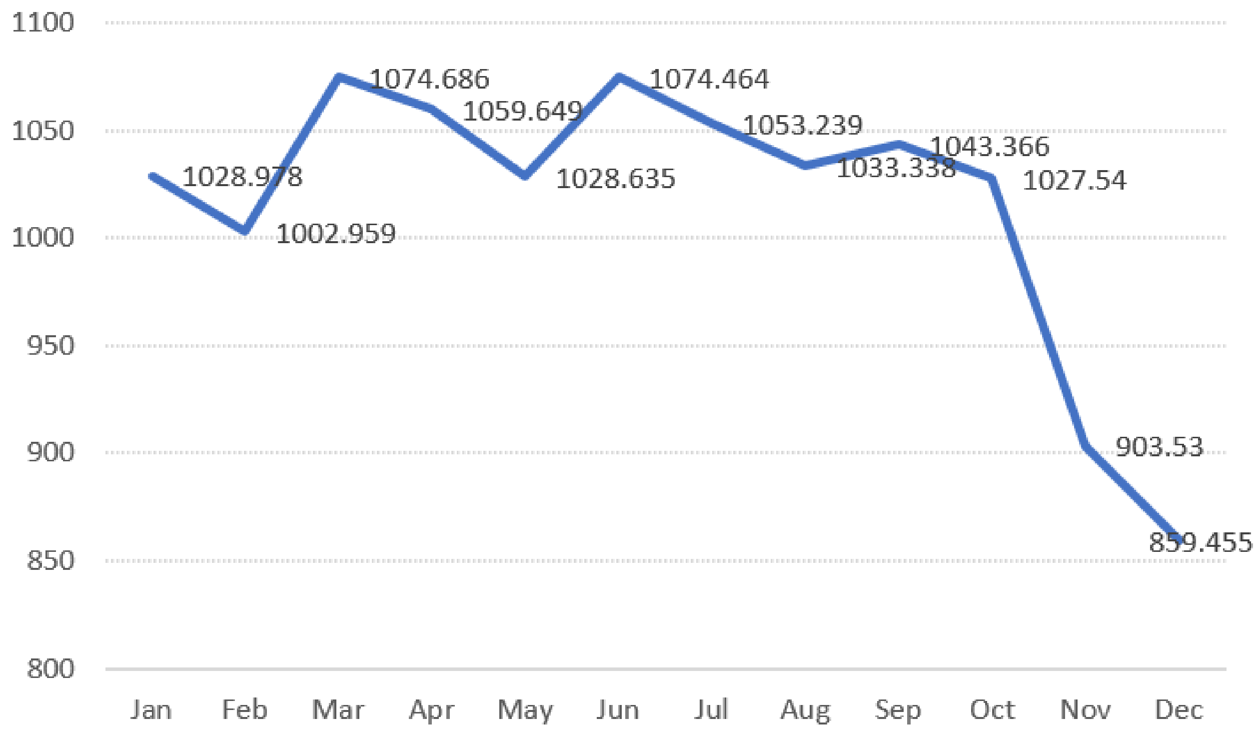


Figure 1: Number of Job postings across states (continued)



(a) Weekday and weekend



(b) Monthly

Figure 2: The average job postings for each month and weekday

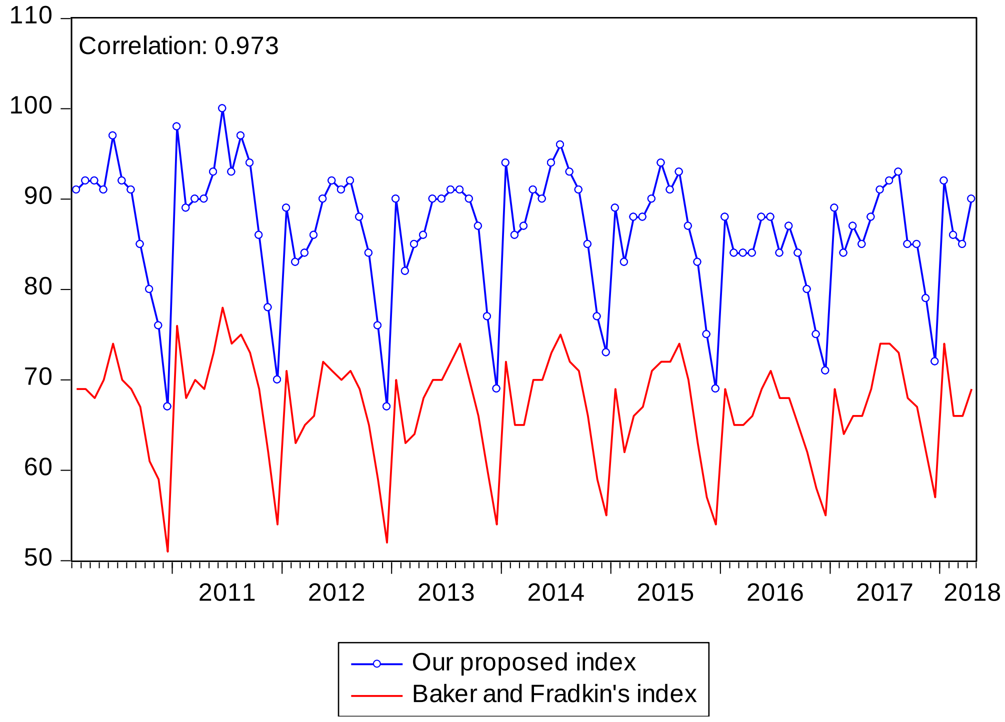


Figure 3. Comparison between job search using English only and other languages

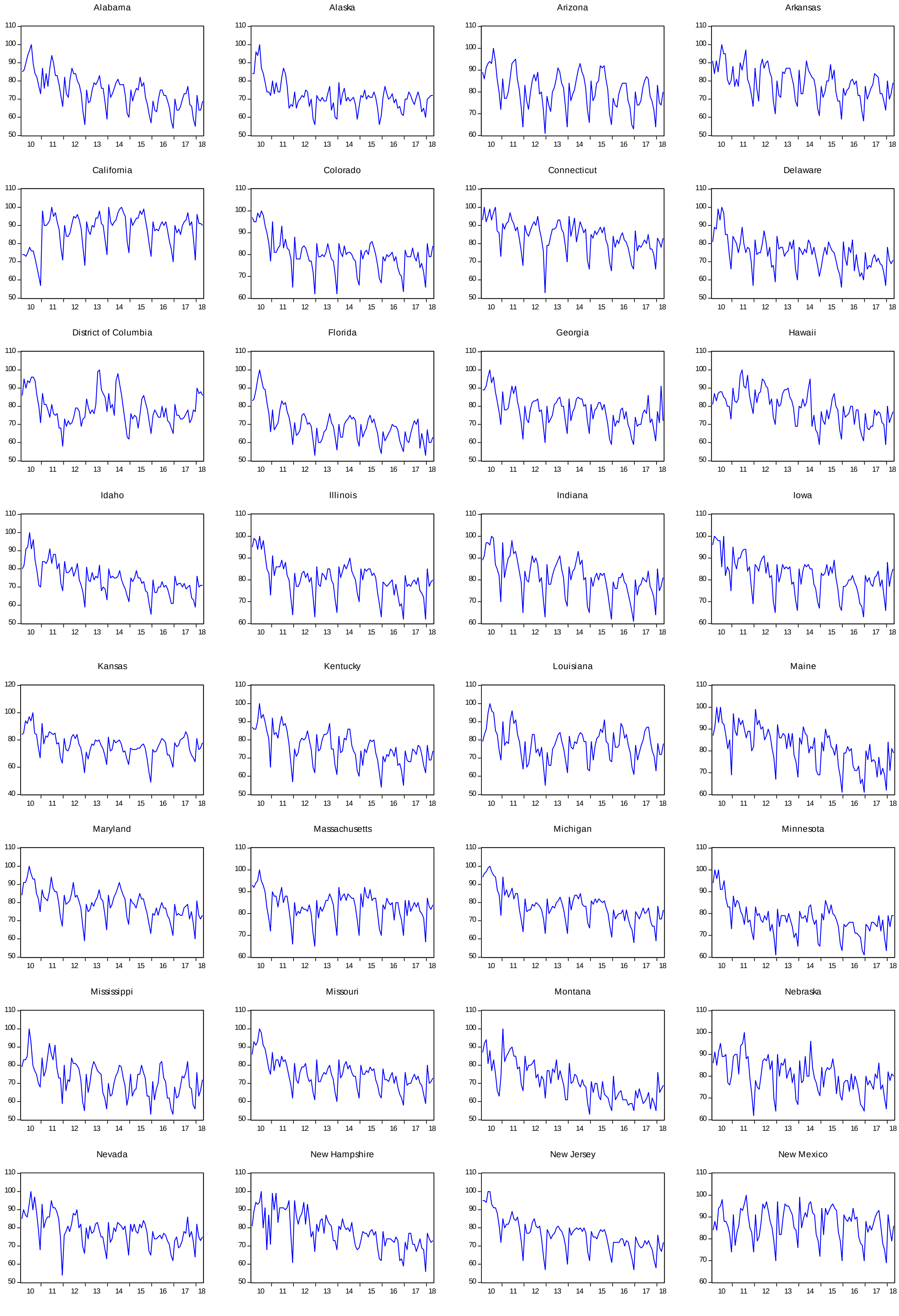


Figure 4: Job search index across states

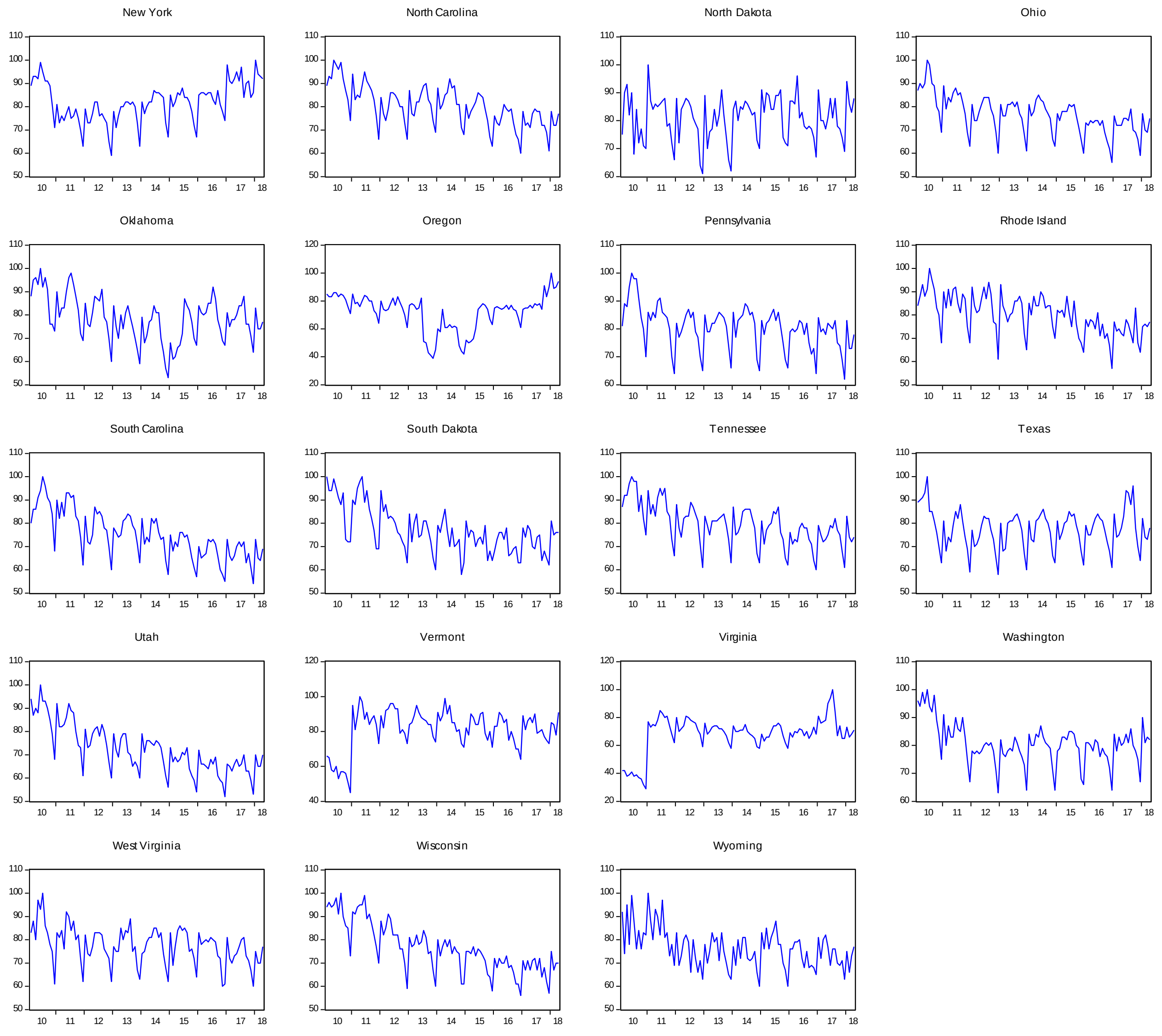


Figure 4: Job search index across states (continued)

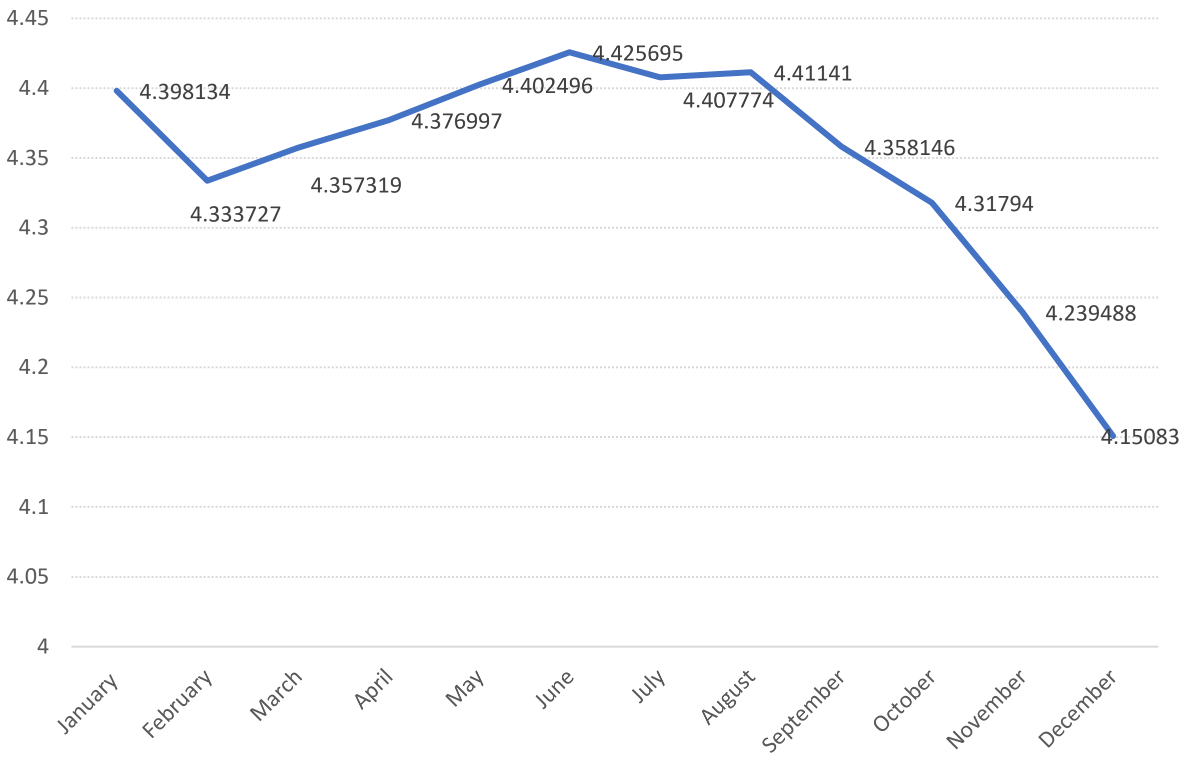


Figure 5: The average job search index for each month

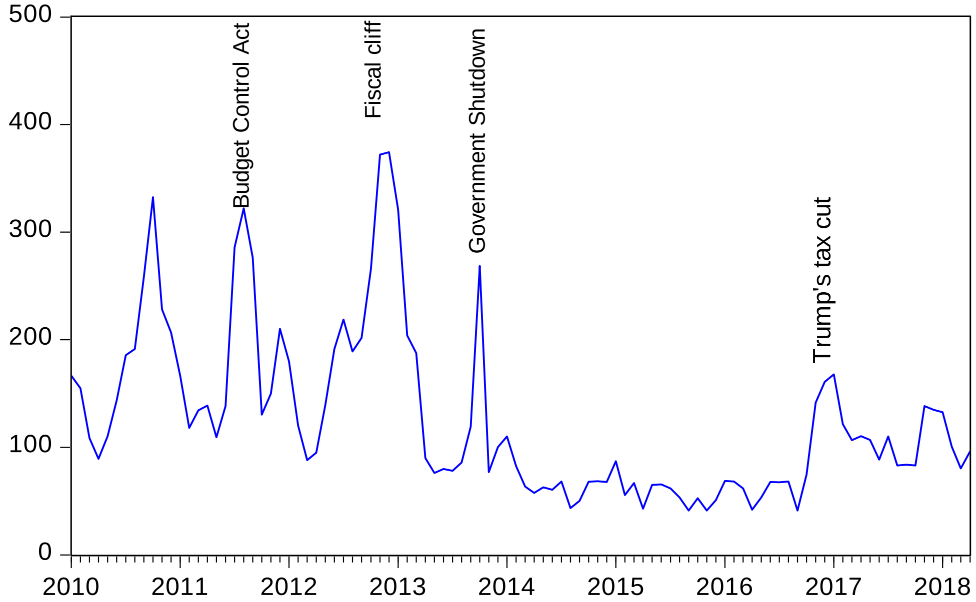
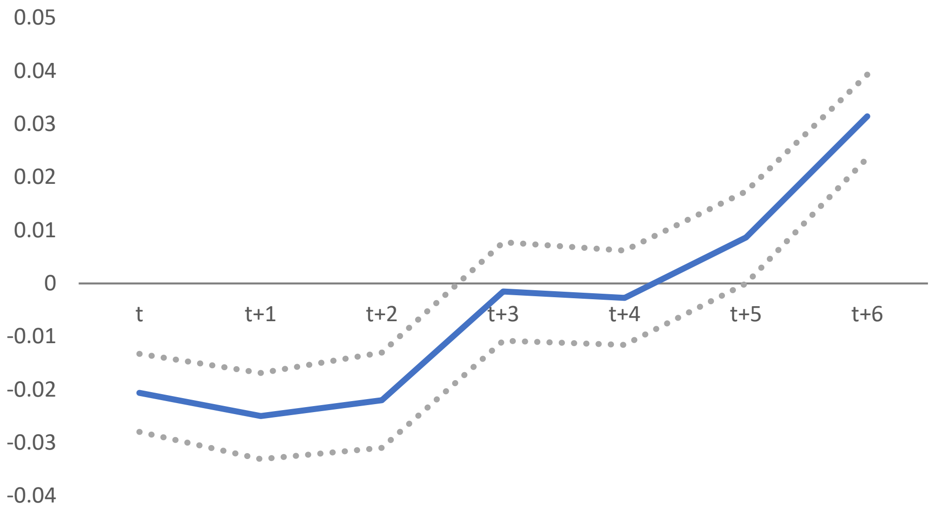
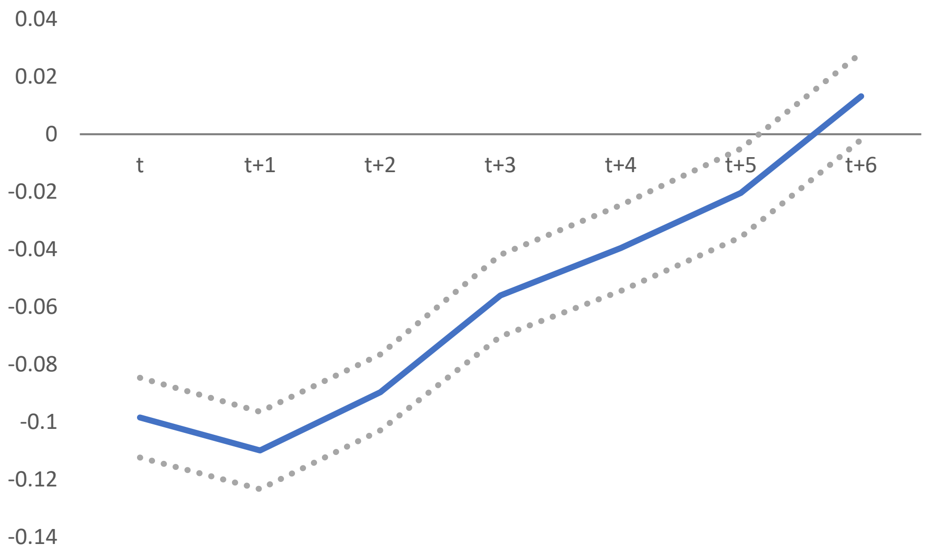


Figure 6. Fiscal policy uncertainty index



(A) Job search



(B) Labour demand

Figure 7. The persistence of FPU effect

Table 1. Baseline results

The dependent variable of the regressions in columns (1) to (5) is state's log job postings, while that in columns (6) to (10) is log of job search index. Independent variables include log of fiscal policy uncertainty (FPU) index, linear time trend, state unemployment rate, squared unemployment rate, and state labour force participation rate. The baseline specification is used and we control for firm fixed effects. Standard errors are clustered at the state and month level and corrected for heteroskedasticity. The clustered standard errors are in parentheses. Sample period is from February 2010 to April 2018. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable: Job postings					Dependent variable: Job search				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
FPU	-0.284***	-0.285***	-0.108***	-0.108***	-0.098***	-0.022***	-0.022***	-0.015***	-0.015***	-0.021***
	(0.025)	(0.006)	(0.029)	(0.007)	(0.007)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Trend			0.006***	0.006***	0.005***			-0.0002***	-0.0002***	-0.001***
			(0.0006)	(0.001)	(0.0004)			(6.65E-05)	(6.01E-05)	(0.0001)
Unemployment					0.103					-0.033
					(0.116)					(0.043)
Squared Unemployment					-0.059*					0.036***
					(0.032)					(0.012)
Labour Force					-1.190***					0.454***
					(0.315)					(0.149)
Constant	7.764***	7.764***	6.209***	6.209***	5.799***	4.245***	4.245***	4.719***	4.719***	4.765***
	(0.116)	(0.029)	(0.180)	(0.045)	(0.181)	(0.015)	(0.014)	(0.020)	(0.018)	(0.069)
Month dummies	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
State FE	No	Yes	No	Yes	Yes	No	Yes	No	Yes	Yes
Observations	5,049	5,049	5,049	5,049	5,049	5,049	5,049	5,049	5,049	5,049
Adj. R-squared	0.025	0.918	0.050	0.943	0.944	0.009	0.171	0.258	0.423	0.431

Table 2. Co-movement of job search activity and job postings across regions

This table reports the average correlation for four main regions. We calculate the simple average using the states within the same region. Appendix A lists the geographical classifications.

	Job Postings	Job search
All States	0.673	0.668
Northeast	0.570	0.567
South	0.781	0.692
Midwest	0.793	0.812
West	0.547	0.600

Table 3. Comparing the effect of FPU on four geographical regions

The dependent variable of the regressions in columns (1) to (4) is state's log job posting numbers, while that in columns (5) to (8) is log of job search index. Independent variables include log of fiscal policy uncertainty (FPU) index, linear time trend, state unemployment rate, squared unemployment rate, and state labour force participation rate. The baseline specification is used and we control for firm fixed effects. Standard errors are clustered at the state and month level and corrected for heteroskedasticity. The clustered standard errors are in parentheses. Sample period is from February 2010 to April 2018. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Appendix A lists the geographical classifications.

	Dependent variable: Job postings				Dependent variable: Job search			
	Northeast	South	Midwest	West	Northeast	South	Midwest	West
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FPU	-0.093*** (0.017)	-0.084*** (0.012)	-0.126*** (0.015)	-0.088*** (0.015)	-0.030*** (0.007)	-0.032*** (0.006)	-0.025*** (0.005)	-0.0003 (0.006)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	891	1,683	1,188	1,287	891	1,683	1,188	1,287
Adj. R-squared	0.960	0.939	0.914	0.951	0.360	0.365	0.556	0.494

Table 4. The role of institutional factors

The dependent variable of the regressions in columns (1) and (2) is state's log job postings, while that in columns (3) and (4) is log of job search index. Independent variables include log of fiscal policy uncertainty (FPU) index, union rating, wage legislation rating, linear time trend, state unemployment rate, squared unemployment rate, and state labour force participation rate. Higher union or wage legislation rating refers to a state that are less likely to affected by union or wage legislation. The baseline specification is used and we control for firm fixed effects. Standard errors are clustered at the state and month level and corrected for heteroskedasticity. The clustered standard errors are in parentheses. Sample period is from February 2010 to April 2018. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Job postings		Job search	
	(1)	(2)	(3)	(4)
FPU	-0.174***	-0.115***	-0.016**	-0.010***
	(0.015)	(0.041)	(0.007)	(0.019)
$FPU \times Union$	0.007***		-0.001	
	(0.001)		(0.0005)	
$Union$	-0.028***		0.009***	
	(0.007)		(0.003)	
$FPU \times Wage\ Legislation$		0.0008		0.002***
		(0.004)		(0.0005)
Wage Legislation		-0.016***		-0.005*
		(0.006)		(0.003)
Other controls	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	4,845	4,845	4,845	4,845
Adj. R-squared	0.945	0.945	0.534	0.541

Table 5. Conditional on monetary policy stance

The dependent variable of the regressions in columns (1) and (2) is state's log job postings, while that in columns (3) and (4) is log of job search index. Independent variables include log of fiscal policy uncertainty (FPU) index, linear time trend, state unemployment rate, squared unemployment rate, and state labour force participation rate. ZLB (non-ZLB) is the period that effective federal funds rate is lower (higher) than 0.25%. The baseline specification is used and we control for firm fixed effects. Standard errors are clustered at the state and month level and corrected for heteroskedasticity. The clustered standard errors are in parentheses. Sample period is from February 2004 to April 2018. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Job postings		Job search	
	(1)	(2)	(3)	(4)
	ZLB	Non-ZLB	ZLB	Non-ZLB
FPU	-0.026**	-0.149***	-0.033***	-0.076***
	(0.010)	(0.011)	(0.004)	(0.005)
Other controls	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	3,621	1,428	3,621	1,428
Adj. R-squared	0.938	0.975	0.415	0.665

Table 6. The role of federal debt level

The dependent variable of the regressions in columns (1) and (2) is state's log job postings, while that in columns (3) and (4) is log of job search index. Independent variables include log of fiscal policy uncertainty (FPU) index, linear time trend, state unemployment rate, squared unemployment rate, and state labour force participation rate. The baseline specification is used and we control for firm fixed effects. We divide our sample into two, based on periods where the ratio of federal debt to GDP was lower than 100% and greater than 100%. Standard errors are clustered at the state and month level and corrected for heteroskedasticity. The clustered standard errors are in parentheses. Sample period is from February 2010 to April 2018. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Job postings		Job search	
	(1)	(2)	(3)	(4)
	High Debt	Low Debt	High Debt	Low Debt
FPU	-0.101***	-0.036**	-0.031***	0.007
	(0.009)	(0.016)	(0.003)	(0.006)
Other controls	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	2,958	2,091	2,958	2,091
Adj. R-squared	0.955	0.939	0.536	0.291

Table 7. Tax or government spending uncertainty

The dependent variable of the regressions in columns (1) to (3) is state's log job postings, while that in columns (4) to (6) is log of job search index. Main independent variables are tax policy uncertainty and/or government spending uncertainty. Control variables include linear time trend, state unemployment rate, squared unemployment rate, and state labour force participation rate. The baseline specification is used and we control for firm fixed effects. Standard errors are clustered at the state and month level and corrected for heteroskedasticity. The clustered standard errors are in parentheses. Sample period is from February 2004 to April 2018. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Job postings			Job search		
	(1)	(2)	(3)	(4)	(5)	(6)
Government spending	-0.033***		-0.168***	-0.014***		-0.007*
	(0.005)		(0.011)	(0.002)		(0.004)
Tax		-0.119***	-0.326***		-0.020***	-0.012*
		(0.007)	(0.016)		(0.003)	(0.006)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,049	5,049	5,049	5,049	5,049	5,049
Adj. R-squared	0.942	0.945	0.947	0.431	0.431	0.431

Table 8. Matching efficiency and fiscal policy uncertainty

The dependent variable of the regressions is state unemployment or labour market tightness, measured by the ratio of number of job postings to unemployment level. Main independent variable is fiscal policy uncertainty (FPU). Control variables are job search and/or job posting. The baseline specification is used and we control for firm fixed effects. Standard errors are clustered at the state and month level and corrected for heteroskedasticity. The clustered standard errors are in parentheses. Sample period is from February 2010 to April 2018. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. U refers to unemployment rate. Tightness refers to labour market tightness (ratio of job posting to unemployment).

	U	U	U	U	Tightness	Tightness
	(1)	(2)	(3)	(4)	(5)	(6)
Log of job postings	-0.517***	-0.474***	-0.406***	-0.366***		
	(0.010)	(0.010)	(0.090)	(0.011)		
Job search		0.695***		0.682***		-1.205***
		(0.033)		(0.031)		(0.068)
FPU			0.134***	0.131***	-0.543***	-0.517***
			(0.005)	(0.005)	(0.009)	(0.009)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,049	5,049	5,049	5,049	5,049	5,049
Adj. R-squared	0.966	0.971	0.970	0.974	0.803	0.821

Table 9. Robustness checks: Endogeneity

The dependent variable of the regressions is state's job search index or number of job postings. Independent variables include fiscal policy uncertainty (FPU) index, linear time trend, state unemployment rate, squared unemployment rate, and state labour force participation rate. The baseline specification is used and we control for firm fixed effects. Panel A reports the results using residual of regressing U.S. FPU on Canadian economic policy uncertainty. Panel B reports the first stage of two-stage least square regression results where partisan conflict index of Azzimonti (2018) is the instrument. Standard errors are clustered at the state and month level and corrected for heteroskedasticity. The clustered standard errors are in parentheses. Sample period is from February 2010 to April 2018. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Using Canadian EPU

	(1)	(2)
	Job Postings	Job search
FPU (residual)	-0.112*** (0.009)	-0.021*** (0.003)
State FE	Yes	Yes
Other controls	Yes	Yes
Constant	Yes	Yes
Observations	5,049	5,049
Adj. R-squared	0.943	0.430

Panel B: Instrumental analysis

	(1)	(2)	(3)
	First Stage	Second stage for job postings	Second Stage for job search
PCI	0.197*** (4.82E-14)		
Fitted FPU		-0.083** (0.041)	-0.168*** (0.017)
State FE	Yes	Yes	Yes
Other controls	Yes	Yes	Yes
Constant	Yes	Yes	Yes
Observations	9,945	5,049	5,049
Adj. R-squared	0.488	0.942	0.436
F-test of exclude instrument	153.406***		

Table 10. Uncertainty versus risk

This table aims to compare the effect of uncertainty and risk on labour market. The dependent variable of the regressions in column (1) and (2) is state's log job postings, while that in column (3) and (4) is log of job search index. Independent variables include fiscal policy uncertainty (FPU) index, linear time trend, state unemployment rate, squared unemployment rate, and state labour force participation rate. All columns include realised equity volatility, which is calculated as the the sum of daily squared stock returns for given month t, or FPU-induced volatility index (VIX) by Baker et al. (2019). The baseline specification is used and we control for firm fixed effects. Standard errors are clustered at the state and month level and corrected for heteroskedasticity. The clustered standard errors are in parentheses. Sample period is from February 2010 to April 2018. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
	Job postings		Job search	
FPU	-0.100***	-0.107***	-0.022***	-0.023***
	(0.010)	(0.009)	(0.003)	(0.004)
RV_t	6.057***		6.179***	
	(1.178)		(0.527)	
RV_{t-1}	0.779		0.272	
	(1.31)		(0.576)	
Fiscal Policy VIX_t		0.016		0.006
		(0.011)		(0.005)
Other controls	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	5,049	5,049	5,049	5,049
Adj. R-squared	0.944	0.944	0.444	0.414

Table 11. Robustness checks: Adding other uncertainty

The dependent variable of the regressions in columns (1) to (3) is state's log job postings, while that in columns (4) to (6) is log of job search index. Independent variables include log of fiscal policy uncertainty (FPU) index, linear time trend, state unemployment rate, squared unemployment rate, and state labour force participation rate. The baseline specification is used and we control for firm fixed effects. Standard errors are clustered at the state and month level and corrected for heteroskedasticity. The clustered standard errors are in parentheses. Sample period is from February 2004 to April 2018. We mainly use one-month, ahead macroeconomic uncertainty (MU), and financial uncertainty (FU) indices by Jurado et al. (2015), as well as geopolitical risk (GPR) index by Caldara and Iacoviello (2018) to represent other uncertainties. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Job postings			Job search		
	(1)	(2)	(3)	(4)	(5)	(6)
FPU	-0.111*** (0.011)	-0.090*** (0.013)	-0.105*** (0.011)	-0.023*** (0.003)	-0.013** (0.003)	-0.021*** (0.003)
MU	-0.636*** (0.120)			-0.108*** (0.023)		
FU		0.177** (0.081)			0.158*** (0.016)	
GPR			-0.038*** (0.010)			-0.0008 (0.004)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,049	5,049	5,049	5,049	5,049	5,049
Adj. R-squared	0.945	0.944	0.944	0.505	0.445	0.437

Table 12. Robustness checks: Outliers, Google market share, and clustering standard errors

In the Panel A and Panel C, the dependent variable of the regressions in columns (1) and (2) is state's log job postings, while that in columns (3) and (4) is log of job search index. Independent variables include fiscal policy uncertainty (FPU) index, linear time trend, state unemployment rate, squared unemployment rate, and state labour force participation rate. The baseline specification is used and we control for firm fixed effects. Standard errors (excluding panel C) are clustered at the state and month level and corrected for heteroskedasticity. The clustered standard errors are in parentheses. Sample period is from February 2004 to April 2018. In the Panel B, The dependent variable is the cyclical component of job search indices or job postings. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Extreme outliers

	Job Postings		Job search	
	(1)	(2)	(3)	(4)
	Winsorised 1%	Winsorised 5%	Winsorised 1%	Winsorised 5%
FPU	-0.098***	-0.105***	-0.020***	-0.018***
	(0.007)	(0.007)	(0.003)	(0.002)
Other controls	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	5,049	5,049	5,049	5,049
Adj. R-squared	0.944	0.944	0.455	0.462

Panel B: Internet users

	(1)	(2)
	Cyclical Job posting	Cyclical Job search
FPU	-0.129***	-0.022***
	(0.017)	(0.003)
Other controls	Yes	Yes
Constant	Yes	Yes
State FE	Yes	Yes
Observations	3,672	3,672
Adj. R-squared	0.152	0.034

Panel C: Clustered by period or state only

	Job posting		Job search	
	(1)	(2)	(3)	(4)
	Cluster by state	Cluster by time	Cluster by state	Cluster by time
FPU	-0.098***	-0.098***	-0.021**	-0.021***
	(0.031)	(0.011)	(0.010)	(0.004)
Other controls	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	5,049	5,049	5,049	5,049
Adj. R-squared	0.944	0.944	0.431	0.431