The Labour Market Effect of Federal 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 states and is also affected by the prevailing monetary policy stance and level of government debt. Industry compositions can explain cross-state variations. Finally, FPU reduces matching efficiency in labour markets. These results are robust to alternative specifications, consideration of the effect of risk on uncertainty, and the endogeneity problem.

JEL classification: D80, H30, J61, J64

Keywords: Job Search; Labour Demand; Job Postings; Policy Uncertainty; Recession; Google Trends

† Thanks to Matthew Notowidigdo, Shixuan Wang, Morten Ravn, James Reade, Carl Singleton, Steven Bosworth, Tho Pham, Kailing Shen, Wenli Xu, Simon Burke, Jie Xie, Binlei Gong, Feng Guo, Yanbin Wen, Yue Wu, Guangrong Ma, and seminar participants at CEC workshops, 3rd Conference on Law & Macroeconomics, and University of Reading for their invaluable comments. All remaining errors are mine.

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 reports 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 recessions (IMF, 2012) and is repeatedly cited as a concern for respondents to the Fed's Beige Book, a qualitative report published by the US Federal Reserve that 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) investigates the effects of policy uncertainty on private investment in developing countries and shows that even a moderate amount of uncertainty can severely 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.

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[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 Cuts and Jobs Act in 2017.

[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 policies 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 adjustments 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, the year that saw the largest increase in trade policy uncertainty. Many other empirical studies show that policy uncertainty decreases capital investment, slows 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, although these factors are important for understanding labour markets. Search effort is a key determinant of employment, as more 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 job vacancies to aggregate job searches (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 searches 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 can affect economies in 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, although they may be uncertain about the timing of these changes. In countries where public finances are relatively sustainable, FPU may increase significantly due to political polarisation and changes in government (Roubini and Sachs, 1989; Perotti and Kontopoulos, 2002). Second, FPU is the largest source of general economic policy uncertainty (see Table 1 in Baker et al., 2016). Third, 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 pure uncertainty (separated from shock realisations) about 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 level of government debt, FPU could generate either positive or negative effects on the economy. Hassett and Metcalf (1999) have a similar argument as they show that tax policy uncertainty can spur or discourage corporate investment depending on expectations of the likelihood of a tax policy switch.

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 previously estimated. 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; Altig et al., 2020). 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 aggregate unemployment (labour supply). We build on this research and provide evidence that FPU decreases both job searches (labour supply) and job postings (labour demand). Moreover, we observe such negative effects vary across states, and industry composition as well as income per capita can explain the variations. 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 factors that determine 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 distant locations. 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 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, while Section 5 focuses on addressing endogeneity issues. Section 6 provides additional robustness checks to support our main findings. Section 7 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 that captures the quasi-universe of all online job ads (Hershbein and Kahn, 2018), with a total of over 150 million US job postings between January 2010 and April 2018. Kuhn et al. (2018) and Hershbein and Kahn (2018) compare this dataset with the JOLTS dataset, another source for job postings, and conclude that the industry composition of the JOLTS vacancies was similar to that of the BGT data, but BGT data contained more detailed information and had 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.[3] Note that our sample period begins in February 2010 since January 2010 data are missing for many states. Because a few days of data are missing, we consider a simple daily average rather than summing up the daily figures to obtain monthly job posting numbers. Clearly, the job posting 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 do 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).

Based on Figure 1, the number of job postings appears to demonstrate seasonality. Moreover, other labour market variables, such as unemployment and the hiring rate, have seasonal behaviour. Thus, it is natural to check whether job postings exhibit seasonality. 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, with the lowest numbers in December. This suggests that firms are typically less likely to adjust their employee structures at the end of year.

2.2 Aggregate job searches

To measure state-level job searches, 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 searches. One advantage of this approach is that it is based on and can track millions of Internet users at any point in time, which better avoids sample bias.[4] Moreover, Stephens-Davidowitz (2014, 2017) and Da et al. (2015) advocate

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

use of internet search data over survey data because it can avoid the potential problems of surveys, such as low response rates. Another advantage of this approach is that it can generate high frequencies and data across geographical areas. Of course, this approach has its limitations; it cannot provide micro information about job seekers, such as gender and age.

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 conclude that more than two-thirds of the respondents had searched for work online. Their study has 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.

We follow their work to use the search topic 'job' as a proxy for aggregate job search behaviour. Our sample data starts in February 2010 and ends in April 2018 because of BGT data availability. Figure 3 plots the job search indices across the 50 US 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 between 2010 to 2014. However, such a decrease is not seen in Oregon, Vermont, or Virginia. Although most state job search levels roughly maintained at similar levels after 2014, some states, such as Idaho, Montana, South Carolina, Utah, and Wisconsin, continued to show further decreases in the level of job search activity.

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

Figure 3 seems to demonstrate seasonality in job searches. To check whether job searches indeed exhibit seasonality, Figure 4 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 in December, which is similar to job posting activity. This is intuitive, because individuals may wait to receive their year-end bonuses before searching for new jobs.

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.[6] They first search for articles containing the terms '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 (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 introduced above, the authors also provide several sub-indices, including the FPU index, by using additional sets of terms. Instead of the above three main sets of terms, they apply one additional term set related to taxes or government spending, such as "federal budget", "defence spending", and "taxes", and count the number of FPU-related articles that contained one or more of these terms.[7] The authors then

[6] Bloom (2014) reviews common approaches to measuring uncertainty. One potential candidate for measuring FPU is based on Jurado et al. (2015). However, applying their approach is limited because economic data at the regional level often have lower frequency. This limitation also exists in tax and government spending data, which are quarterly or yearly observations.
[7] The actual terms used to develop the FPU index can be found at http://www.policyuncertainty.com/categorical_terms.html.

compute 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 normalise the resulting series. Finally, they aggregate 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 is 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 5 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. One worth to note is that this FPU index measures policy uncertainty from federal government not state-level government. It is noticeable that FPU spikes correspond to several policy events. For example, the spike in August 2011 relates to the enactment of the Budget Control Act. Each of the fiscal cliffs in 2012, the government shutdown in 2013, and more recently, Trump's 2017 tax cut reform sparked a spike in FPU.

3 Empirical approach

The baseline empirical model is specified as follows:

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

where *i* denotes the state; *t* denotes the time; $Y_{i,t}$ is either the job search index or the 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. $X_{i,t}$ is a set of controls, including the growth rate of gross state production (GSP), state unemployment rate, squared term of the unemployment rate, and labour force participation.[8] 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 strong negative relationship with job vacancies as per the standard search-matching theory (see Pissarides, 1985; Mortensen and Pissarides 1994).[9] Following Petersen (2009), standard errors are clustered by month and state to control for potential cross-sectional and serial correlation in the error term.

β_1 is the primary variable of interest. 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

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

waiting increases during uncertain times, leading them to postpone finance and investment decisions (see, for example, Bernanke 1983; Abel and Eberly, 1996; Bloom, 2009; Leduc and Liu, 2016). 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 on job search.[10]

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.

4 Main results

This section focuses on the effect of FPU on job searches and labour demand. Instead of baseline results, we also provide several additional analyses to show how the effects of FPU vary under different conditions.

[10] 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.

4.1 Baseline results

Table 1 reports the estimation results of our baseline regression model. Columns (1) to (5) display the results for job postings. Column (1) reports the effect of FPU on the number of job postings without any controls or fixed effects. We find that the number of job postings negatively responds to increasing FPU. 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 strong during recent well-known fiscal events, such as the 2013 government shutdown (FPU index more than doubled within a year). When the state fixed effects and monthly dummy variables (columns (2) and (3)) are included in the model, the impact of FPU remains negative and significant at the 1% level. The fourth column shows the outcomes when we control for state GSP growth rate, unemployment rates and labour force participation. We observe that the coefficient of FPU remains significantly negative at the 1% level, with a magnitude of -0.106, showing that a 1% increase in FPU leads to around 0.1% decrease in job posting. This result meets our expectation that firms tend to reduce or delay their labour demand when uncertainty is high. Last, we consider the nonlinear effect of unemployment on job postings by including the square of the unemployment rate. The coefficient of FPU remains significantly negative and slightly changes compared to that in column (4). This result is consistent with the real option theory that firms tend to delay hiring decisions during high uncertainty (e.g. Bloom, 2009; Leduc and Liu, 2016).

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 state fixed effects are included in the model (column (7)), the FPU effect remains negative and significant at the 1% level. This finding is robust after including month dummies. The FPU coefficient in column (8) is -0.031 with a t-statistic of around -10 (-0.031/0.0003). Last, we include the unemployment rate and labour force participation in the equation and observe that the FPU effect on job searches is significantly negative with a coefficient of -0.019 and a t-statistic smaller than -6 (see columns 9 and 10). Given the evidence that job postings are lower during high FPU, the result of job search is consistent with the prediction from standard search and matching models, implying that during bad times, the return on job search effort is lower, leading to lower effort.

4.2 Subsample analysis

The monetary policy stance

As documented in the literature, one important condition for understanding the effect of FPU is the monetary policy stance. Bi et al. (2013) suggest that FPU could generate positive or negative effects for the economy, depending on the monetary policy stance. Johannsen (2014) further argues that FPU causes large negative effects on investment, consumption, and output in times of zero lower bounds (ZLB), but only modest effects during non-ZLB period.[11] When there is economic contraction, risk-averse households desire to work and save more, which cause inflation to fall. When ZLB binds, associated increases in real interest rate would discourage investment and consumption.

[11] The ZLB rate refers to a time where interest rates have fallen as far as they can. Please see https://www.economicshelp.org/blog/7603/economics/zero-lower-bound-rate-zlb/ for a brief introduction to ZLB.

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%.[12] The results listed in Table 2 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 job posting during non-ZLB periods. A 1% increase in FPU leads to around 0.15% decrease in the number of job postings, which is much greater than that of the ZLB period (0.049%).

Similarly, our results indicate that FPU has a stronger effect on job searches in non-ZLB periods. 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 searches during ZLB periods are also consistent with Potter's (2020) results, which show that job searches decline monotonically during the 2007–09 financial crisis. We also perform the Wald test to examine the significance of the different effects of FPU on labour markets for ZLB and non-ZLB periods. The Wald test results confirm that FPU has a greater impact on labour markets in the time of ZLB period.

The role of debt level

[12] The data are collected from the Federal Reserve Economic Data database.

The effect of FPU on an economy may depend on the level of federal 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 its explanation. Other studies, including Sutherland (1997) and Perotti (1999), all show that the effects of fiscal policy on the economy vary depending on public debt. 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 3 suggest that FPU has a significant negative impact on labour demand when the level of federal debt is high. A 1% increase in FPU leads to around 0.096% decrease in the number of job postings, which is much stronger than that of the low debt period (decrease by 0.083%). The Wald test result shows such a difference is significant. Similarly, our results indicate that FPU has a stronger effect on job searches in high debt periods. They suggest that a 1% increase in FPU leads to a 0.030% decrease in job searches. However, during periods of low federal debt levels, FPU has an insignificant impact on job searches. Wald test results further confirm that the effect of FPU on job search is more significant in high-debt period. In sum, our results show that the magnitude of FPU's effect on the 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 that has not yet been considered is isolating the effect of government spending and taxes, 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 4 show that both job seekers and firms are more sensitive to tax policy uncertainty. This result is similar to the finding of Alesina and Ardagna (2010) who show that tax cuts are more likely to increase growth than increases in government spending. 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 greater uncertainty increases the real-option value of waiting for a rebound in approximately six months. We respectively run the baseline regression using the future values 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 6, with the corresponding 95% confidence intervals.[13]

Job postings initially drop at time t, with the largest drop at $t+1$. This indicates that because 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 time t. The negative effect of FPU on job postings then 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

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

decreases initially, at time *t*, in response to rising FPU. The negative effect of FPU on job searches peaks at time *t+2* and gradually becomes weaker.

4.3 Cross-sectional analysis

Regions within a country are generally not homogenous economic units. Each region might have varying levels of fiscal, political, and economic disaggregation. As emphasised by the literature (e.g. Blanchard and Katz, 1992; Montgomery, 1993; Decressin and Fatas, 1995; Carlino and DeFina, 1998; Moretti, 2011; Dao et al., 2017), it is important to understand the heterogeneity of local labour markets. There are at least two reasons for doing this. First, understanding the evolution of local labour markets can help local governments tailor their policies to improve these markets. Second, as shown by Leduc and Liu (2016) and Mumtaz et al. (2018), the heterogeneity of local labour-market rigidity can lead to different responses to macroeconomic shocks. This issue is perhaps more prominent in the United States because state governments can have their own legislation on top of the federal law. This section aims to examine the heterogeneity of state labour markets by examining job positing and job search behaviours.

One straightforward approach to investigate the co-movement of variables is to compute its pairwise correlations and the common variance explained by the first component identified through a principal component analysis (PCA). Instead of providing results for each state, we summarise the findings for nine regions based on the United States Census Bureau. The appendices report the classification details.[14]

[14] Due to limited space, the results of pairwise correlation among states are available upon request.

Table 5 reports the average pairwise correlation of the job search index and the common variance explained by the first component identified through a PCA. We report average pairwise correlations among states within each region. Generally, the aggregate regional job search is highly correlated, with an average correlation of over 65% among all states. In addition, Table 5 shows that job searches are significantly more synchronised in the East North Central, and East South Central regions, with an average correlation of around 90%. Such a high correlation is also observed when examining the number of job postings (see column 3 of Table 5). We observe an average of 60% correlation for all states, wherein the East North Central and Middle Atlantic are the highest at nearly 85%. Similar findings are obtained when analysing the common variance explained by the first component identified through a PCA (columns 2 and 4). However, the correlation coefficients are particularly low in the Pacific region, below 40%, in both job search and job posting behaviours. This indicates that states' labour markets within the Pacific region vary considerably.

We next estimate the effect of FPU on state labour markets by estimating the time-series regression separately for each state. Table 6 reports the estimated coefficients of FPU for each state. Table 6 shows that FPU has a significant negative effect on job postings but with differing economic magnitude across regions and that there is a stronger effect in certain states including Louisiana, Alabama, Montana, and Nebraska, regardless of the economic or statistical magnitude. Furthermore, the result indicates that a 1% increase in FPU leads to more than 0.18% decrease in job postings in these states. For some states, such as Nevada, Delaware, and Missouri, FPU has insignificant impact on job postings.

Regarding the effect of FPU on job searches, the results are similar. The results generally indicate that most states experience drops in job search levels when FPU increases, but with smaller economic magnitude. The coefficients are generally between -0.02 and -0.06. Mississippi, Connecticut, and New Jersey are particularly sensitive to FPU shocks compared to the other states. For a 1% increase in FPU, job searches decrease by more than 0.06% for these three states.

Given the evidence that different states have different responses to FPU, possible factors driving this heterogeneity are worth investigating. One potential factor is industry composition. As shown by Choi et al. (2018), and Mumtaz et al. (2018), manufacturing firms are more sensitive to aggregate economic uncertainty shocks. Moreover, Mumtaz et al. (2020) further show that manufacturing firms are more dependent on national government spending. Thus, we consider state manufacturing employment share as a potential factor.

Other than manufacturing firms, we also consider the employment share of mining and construction industry. As we observed, the FPU coefficients seem larger in the Southern part of United States, with the prevalence of mining and construction industry. Again Mumtaz et al. (2020) also argue that mining sector is more dependent on national government spending because it is more influenced by commodity price cycle. Thus, we include state mining and construction employment share as a potential factor.

Third, it is possible that institutional factors can explain 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.[15] In a more rigid region, the effect of uncertainty may be amplified. We use the labour freedom score from the Fraser Institute as a proxy for labour market rigidity. The higher rating of

[15] 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.

these scores shows more economic freedom in labour markets (i.e. less rigidity). Finally, we consider the average income per capita as a proxy for economic development of each state.

Table 7 reports the cross-sectional regression results wherein state FPU coefficients are the dependent variable. We find that higher employment shares of manufacturing, and mining and construction industries have a significant negative association with FPU coefficients. This reflects that a state with higher share of manufacturing and/or mining and construction industries could experience a larger drop in job postings in the face of FPU shock. Average income per capita also can explain some cross-sectional variation in job postings in response to FPU shock. Higher income per capita can mitigate the negative effect of FPU on job postings.

Regarding the case of job search, the higher employment share of mining and construction industry can mitigate the negative effect of FPU shocks. Other factors seem unable to explain cross-section variations in job search's response to FPU. We also do not find evidence to support the view that labour market rigidity plays an important role in determining the magnitude of FPU shocks on labour markets.

4.4 Matching efficiency and fiscal policy uncertainty

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

$$U_{j,t} = \beta_0 + \beta_1 FPU_t + \beta_2 V_{j,t} + job\ search_{j,t} + u_j + \varepsilon_{j,t}, \qquad (2)$$

$$VU_{j,t} = \beta_0 + \beta_1 FPU_t + job\ search_{j,t} + u_j + \varepsilon_{j,t}, \qquad (3)$$

The first model assesses whether the coefficient of job postings ($V_{j,t}$) is different before and after adding the FPU index, while the second one assesses whether FPU affects the job postings-unemployment ratio (labour market tightness, $VU_{j,t}$).[16] Note that the log of unemployment numbers is applied, rather than the unemployment rate, because data were only available for the number of job postings and not the job postings rate or job vacancies rate. The coefficient of FPU in equation (2) 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 that drives 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 Mitigating endogeneity concerns

So far, we have documented a strong association between FPU and job searches (job postings). However, there may be an endogeneity problem in our analysis. For example, if the economy is hit by a shock that increases unemployment, then policymakers need to determine whether or how to respond; thus, fiscal-policy uncertainty may be a consequence of changing labour-market condition. This section focuses on addressing endogeneity concerns to establish the

[16] 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 the results are qualitatively the same.

causal effect of FPU on these two variables. The endogeneity concerns may come from omitted variables or reverse causality. We first control for more variables to reduce the concern of omitted variables. Then we try our best to address reverse causality issue.

Considering economic uncertainty

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 the 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.[17] 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:

$$FPU_t = \alpha + \beta \cdot Canadian\ EPU_t + \varepsilon_t, \tag{4}$$

where the residual of regression (4), (ε_t), captures FPU that is orthogonal to Canadian EPU. This residual is used to replace FPU in equation (1). Panel A of Table 9 shows a negative and significant relationship at the 1% level between FPU, proxied by the residual, and job searches (postings).

However, one can probably argue that Canadian policy uncertainty may be too dependent on political developments in the US, so the residual FPU still reflects underlying general economic conditions. We thus include two US economic uncertainty indices developed by Jurado et al.

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

(2015)—macroeconomic and financial uncertainty— as well as Baker et al.'s (2016) general EPU index in our regressions to further reduce the concern that our results are driven by economic uncertainty or other types of uncertainties.[18] Panel B of Table 9 shows the estimated results. Overall, the FPU effect on job searches and labour demand remains significantly negative at the 1% level. These findings show that the observed effects are not confounded by economic uncertainties. One interesting observation is that general EPU increases job searches and postings. This may imply that not all policy uncertainties have negative effects on labour markets.

Using national security events as an instrument

A classical approach to addressing the endogeneity problem is using instrumental variables. A proper instrument should be highly correlated with FPU and able to affect labour market only through this relationship. We propose using national security uncertainty as such a variable. National security uncertainty is positively correlated with FPU because it affects whether the government should change defence spending, which is part of federal government spending. For example, news from National Defense discusses the possibility that national defence would change owing to the tension between the US and Iran.[19] Ramey (2011), and Nakamura and Steinsson (2014) also employ military procurement spending as an exogenous measure of government spending and estimate the effect of government spending on the economy. Nevertheless, individual job searches or firm hiring decisions are less likely to directly correlate with national security spending. We thus believe this is an appropriate instrument that satisfies the exclusion restriction.

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[18] The macroeconomic and financial uncertainty indices are econometric estimates based on various economic activity variables. Jurado et al. (2015) provide 1-month, 3-month, and 12-month ahead indices. We use the 1-month ahead index. We also test using the 6-month and 12-month indices and find that the qualitative conclusions do not change.
[19] https://www.nationaldefensemagazine.org/articles/2020/1/27/tensions-with-iran-could-impact-defense-spending.

We adopt national security uncertainty index created by Baker et al. (2016) as an instrument. This index is also a sub-index of aggregate EPU index. They typically use keywords, such as military conflict, terrorism, terror, and 9/11, to construct the national security uncertainty index. As both FPU and national security indices are national time series, we use time-series regression to perform the first-stage estimation, which can help to avoid the problem in traditional two-stage least-squares methodology, which would overstate the correlation between the endogenous variable and its instrument. The first-stage estimation is specified as follows

$$FPU_t = \alpha + \beta \cdot NS_t + \gamma \cdot X_t + \varepsilon_t. \tag{5}$$

where NS_t is the national security uncertainty index, and X_t refers to all the control variables used in the baseline regression. Then, we re-estimate the average effect of FPU on labour markets using the fitted values from Equation (5) to capture the exogenous variation in FPU. As shown in the first column in Table 10, a significant and positive coefficient of NS_t suggests that more national security uncertainty is indeed significantly associated with higher FPU. In the second stage (columns (2) and (3)), the fitted FPU variable has a significant negative effect at the 1% level on both job searches and job postings. The results suggest even more stronger effect of FPU on both job searches and postings. Overall, based on the above analyses, the negative FPU effect on job searches and job postings is not tainted by potential endogeneity.

Using presidential elections as a proxy for FPU

Elections are the literature’s traditional measure of policy uncertainty. During the electoral process, politicians have different preferences for policies, so election timing introduces uncertainty about government policies. The advantage of this approach is that elections are usually pre-scheduled (at least in the US) and thus can be viewed as mostly exogenous events where policy uncertainty arises.[20] Prior studies have used elections to proxy for political uncertainty. For example, Julio and Yook (2012, 2016) use national election dummies as proxies for policy uncertainty and show that corporate capital investment and foreign direct investment, respectively, drop significantly around domestic elections. Bhattacharya et al. (2017) show that innovation activities also drop significantly during times of national elections.[21]

We employ a presidential election dummy that equals one during the two months before and in the month of a presidential election and zero otherwise, to proxy for FPU (at least partially).[22] We concentrate on the presidential election because our focus in this study is federal FPU rather than local government FPU. We estimate the baseline specification but replace FPU with a dummy variable for presidential elections. The estimated coefficients in Table 11 are significantly negative, providing additional support for the hypothesis that higher FPU leads to reduced job search effort and firms' labour demand.

6 Additional robustness checks

In this subsection, we present a battery of robustness checks: isolating the effect of uncertainty from risk, considering alternative FPU measures, considering extreme outliers, investigating the effects of Google's market share and increasing Internet usage, and analysing different clustering methods for standard errors.[23]

[20] The main reason we do not use elections in our primary analysis is because they occur at a low frequency (either every two or four years in the US), and election uncertainty contains other types of policy uncertainty, such as trade policy uncertainty.
[21] Other studies also use gubernational elections to proxy for local policy uncertainty, such as Jens (2017), Gao et al. (2019), and Atanassov et al. (2020).
[22] The results are robust if we set the election dummy equal to one for the month of presidential elections and zero otherwise.
[23] 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 based on the Philadelphia Fed's Survey of Professional Forecasters (SPF), can affect the labour market. Our results are qualitatively the same and are available upon request.

Risk versus uncertainty

It is important to disentangle the effect of labour market uncertainty 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 the implied and realised volatility of the S&P 500 index as proxies 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 12 provides the estimation results after including realised volatility. The FPU coefficients in columns (1) and (3) are significantly negative. This indicates that when we disentangle FPU from risk (even partially), the result still shows that FPU decreases both job searches and postings, and the estimated coefficients are similar to our baseline results.

Another approach we employ to disentangle 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 driving effect of economic news on this fiscal policy-related EMV index. We add this index to our baseline regression and re-estimate it. The results still support the view that FPU significantly decreases aggregate job searches and labour demand (see columns (2) and (4) in Table 12).

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's risk has no significant effect on either variable. The FPU-related risk measures are also not significant for either variable.

Alternative measure of FPU

To verify that our results do not depend on the method used to measure FPU, we employ two alternative measurements. The first is the tax code expiration data from the Congressional Budget Office. This temporary tax code is an appropriate proxy for tax policy uncertainty because Congress often extends the code at the last minute, which creates uncertainty for firms and households (see Baker et al., 2016 for a discussion). Another proxy for government spending uncertainty is from the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters. We use dispersion in the individual-level data of the two forecast variables that are directly related to government spending: purchases of goods and services by state and local governments and purchases of goods and services by the federal government.

Using these two measures for FPU, we re-estimate the baseline regression. Table 13 reports the estimation results. The results indicate that our baseline results are not driven by the choice of the FPU measure because we observe a negative relationship between FPU and job searches or job postings.

Extreme Outliers

Next, we address the issue of outliers because we observe that FPU sharply increases in 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 14, show that the negative relationship between job searches (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).[24] The regression results for the cyclical component and FPU are summarised in Panel B. Overall, our results remain robust, also implying that FPU can explain the cyclical behaviour of job searches and job postings.

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, the FPU index does not vary by state. To reduce this concern, we respectively re-estimate the baseline model using different clustering methods, especially clustering errors by time only, which could increase the standard errors substantially given the serial correlation in FPU. The results reported in Panel C of Table 14 remain robust.

[24] 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.

7 Conclusion

In this study, we investigate 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 find that FPU, especially tax policy uncertainty, has a negative effect on both job searches and job postings. FPU's negative effect on job searches and postings is subject to the monetary policy stance and level of government debt. Moreover, we observe that coefficients of FPU vary across states, and industry composition and income per capita can explain such variations. Finally, FPU also reduces matching efficiency in local labour markets.

Our 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, manufacturing, and mining and construction firms are more vulnerable to FPU. Third, it is important to consider the debt level and monetary policy when evaluating the effect of fiscal policy on the economy.

One limitation of this study is that we only consider FPU in the federal government, as the news-based FPU index focuses on measuring policy uncertainty from the federal government. One worthwhile extension is to compare the effects of FPU in local governments and in the federal government on the economy, where the former might have a different impact on the economy, or even mitigate the effect of federal fiscal policy (Aizenman and Marion, 1993).

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Appendix A

New England Region: Maine, New Hampshire, Vermont, Massachusetts, Rhode Island, Connecticut

Middle Atlantic Region: New York, New Jersey, Pennsylvania

East North Central Region: Ohio, Indiana, Illinois, Michigan, Wisconsin

West North Central Region: Minnesota, Iowa, Missouri, North Dakota, South Dakota, Nebraska, Kansas

South Atlantic Region: Delaware, Maryland, District of Columbia, Virginia, West Virginia, North Carolina, South Carolina, Georgia, Florida

East South Central Region: Kentucky, Tennessee, Alabama, Mississippi

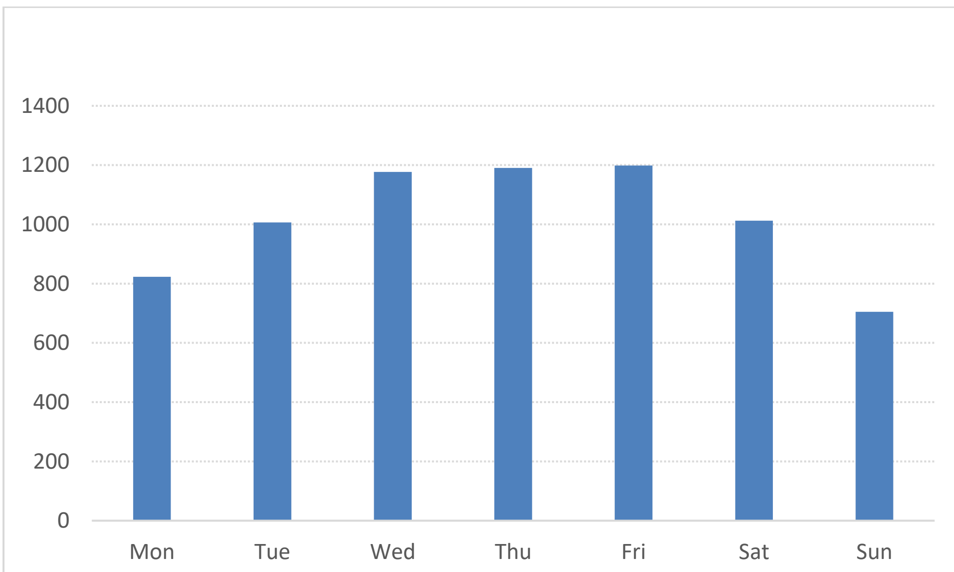
West South Central Region: Arkansas, Louisiana, Oklahoma, Texas

Mountain Region: Montana, Idaho, Wyoming, Colorado, New Mexico, Arizona, Utah, Nevada

Pacific Region: Washington, Oregon, California, Alaska, Hawaii

Appendix B Week and weekend effects

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



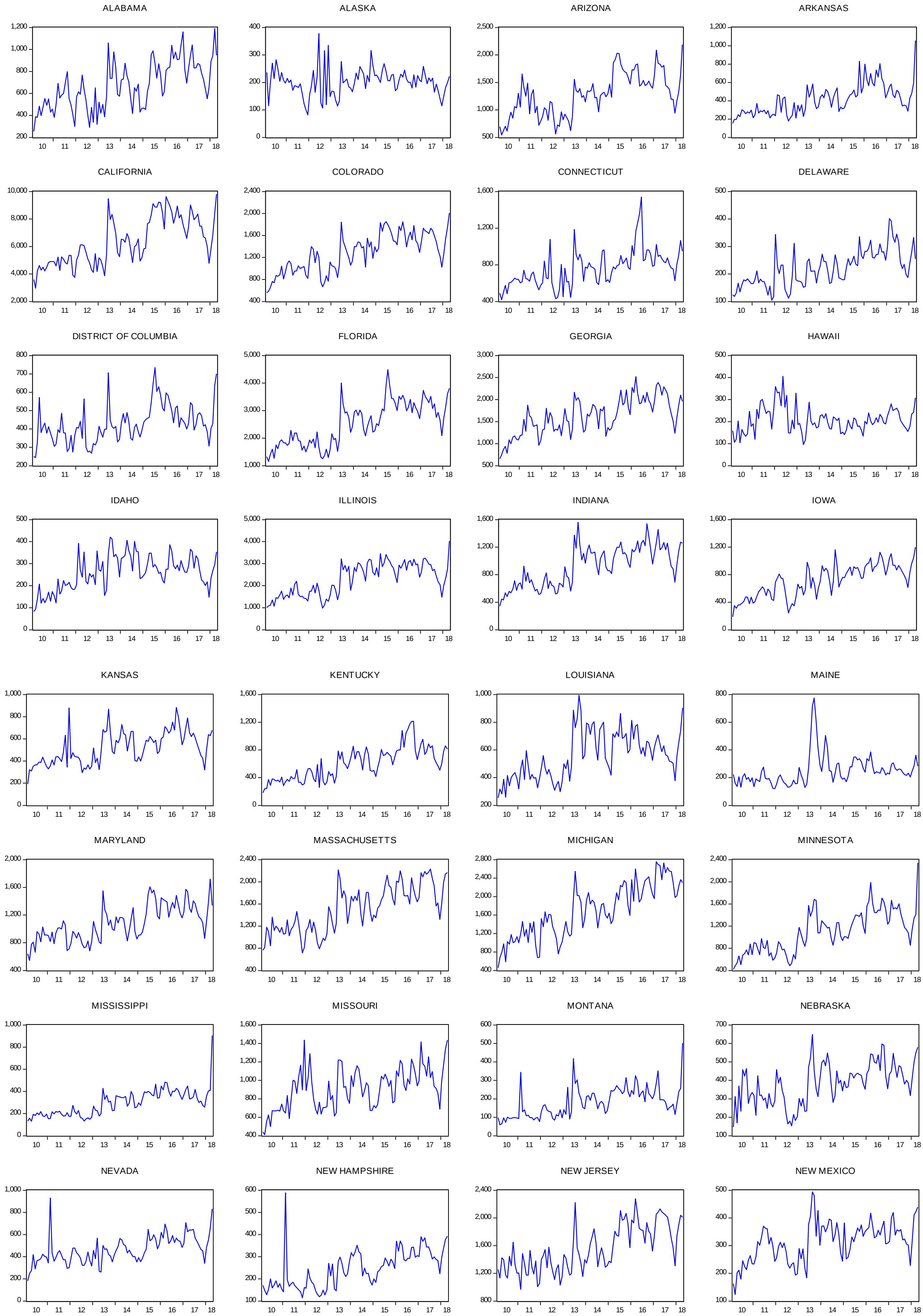


Figure 1: Number of Job postings across states

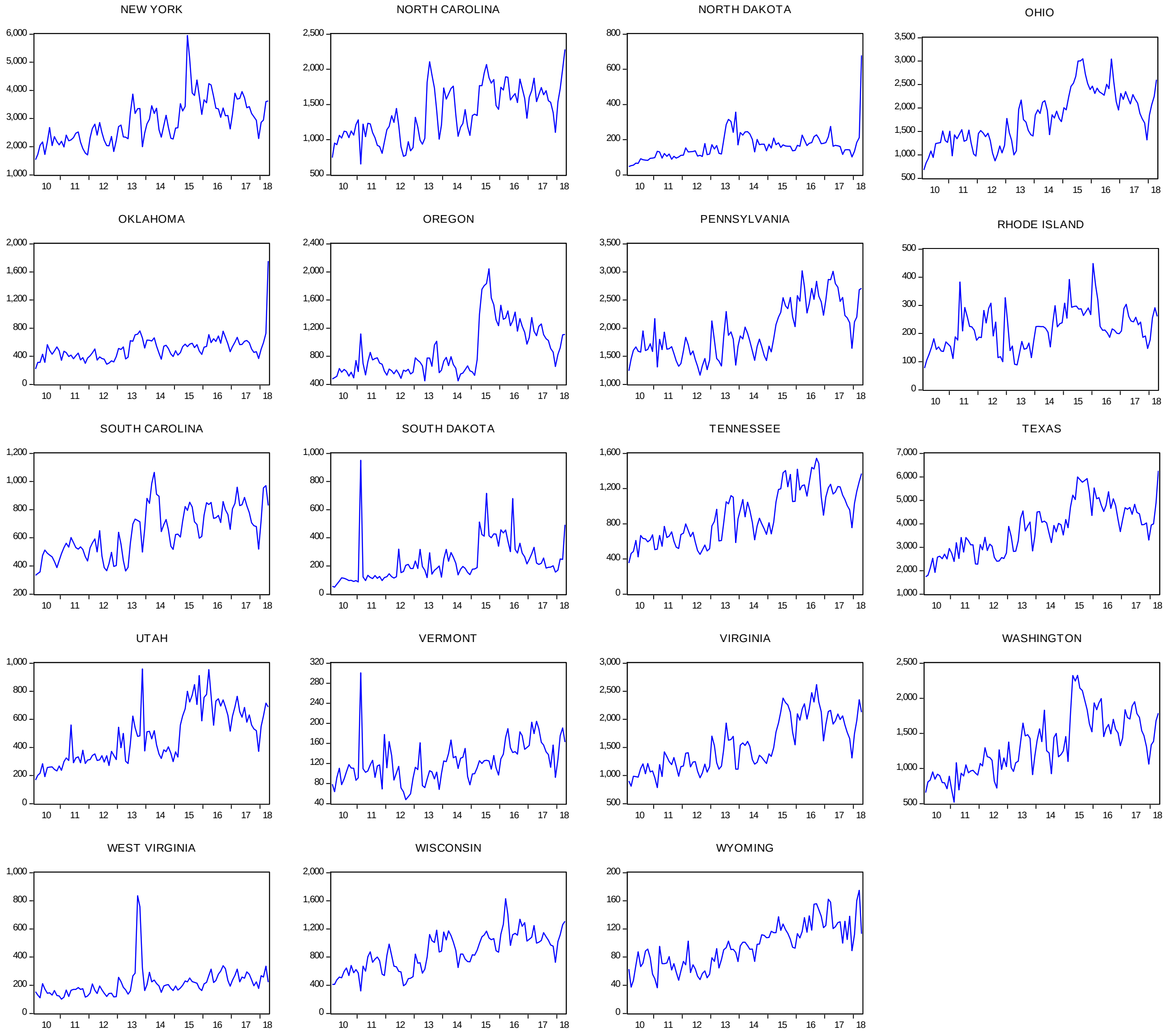


Figure 1: Number of Job postings across states (continued)

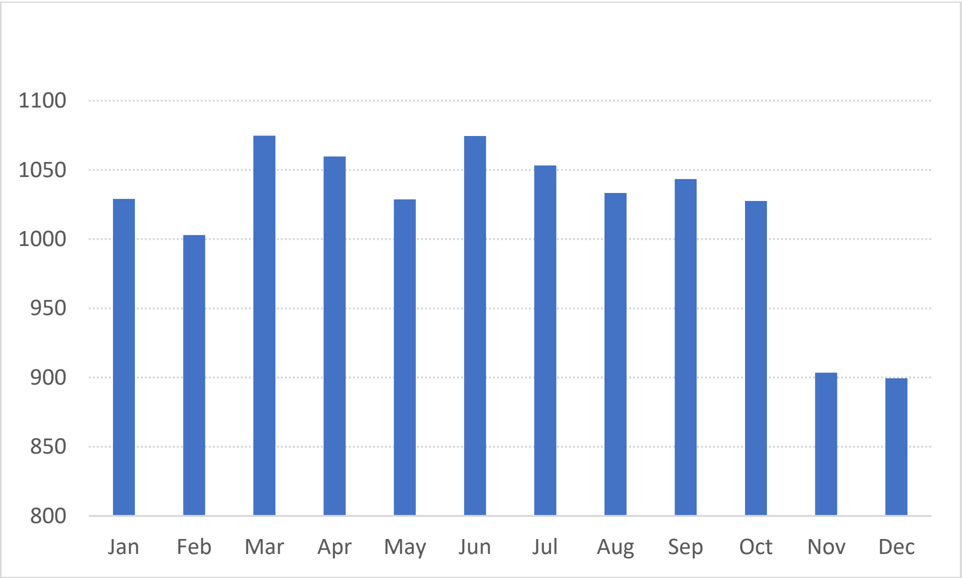


Figure 2: The average job postings for each month

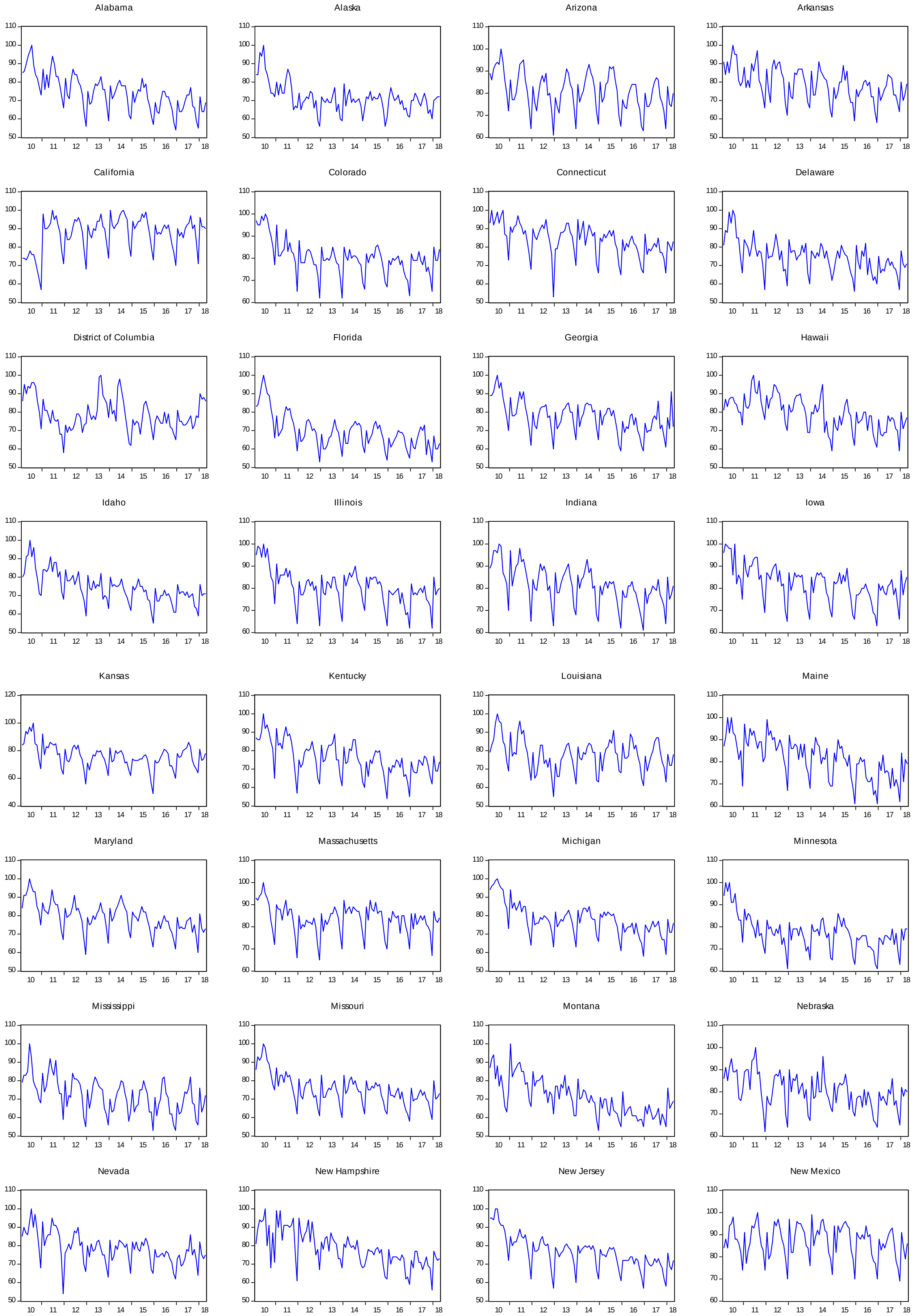


Figure 3: Job search index across states

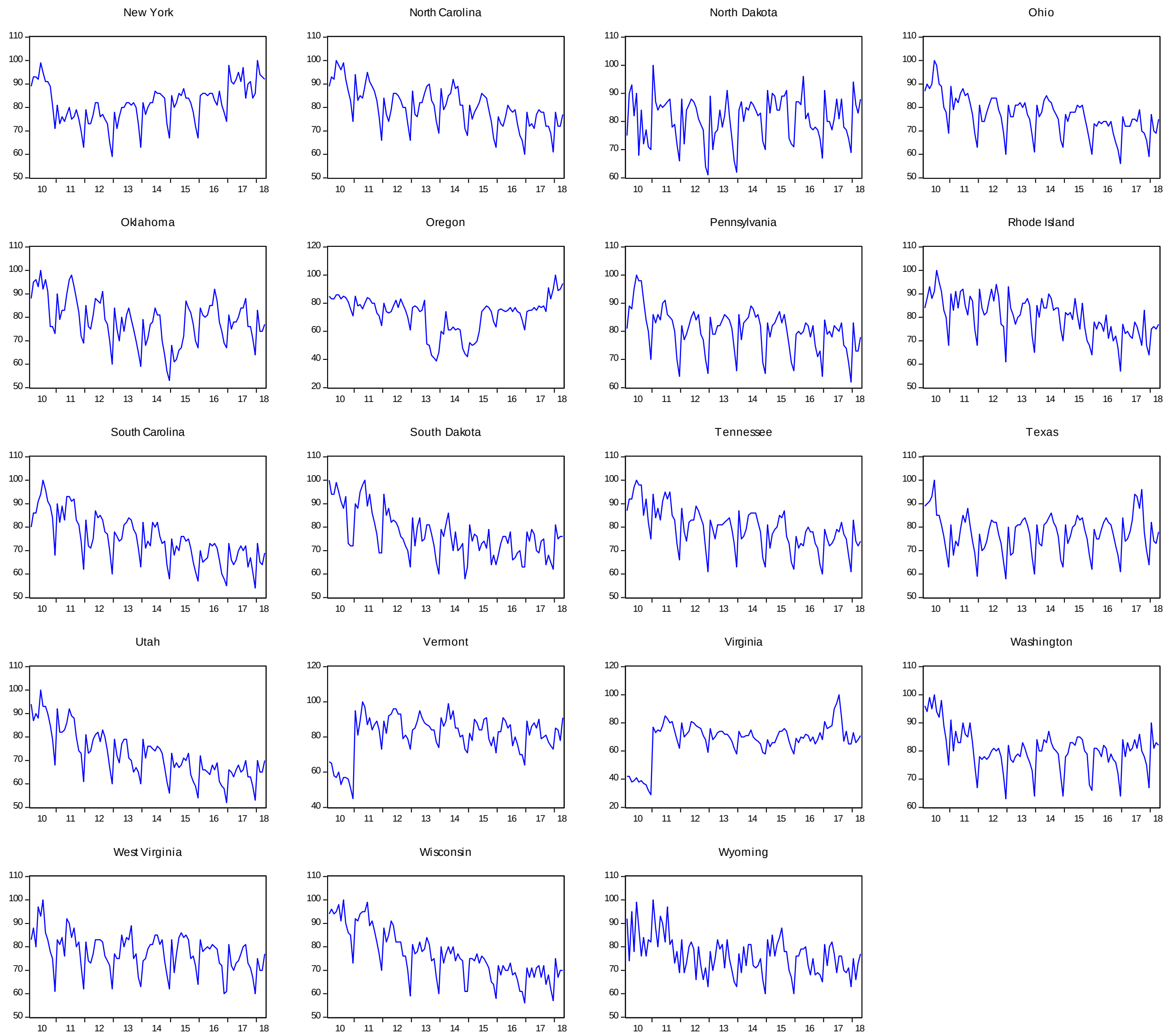


Figure 3: Job search index across states (continued)

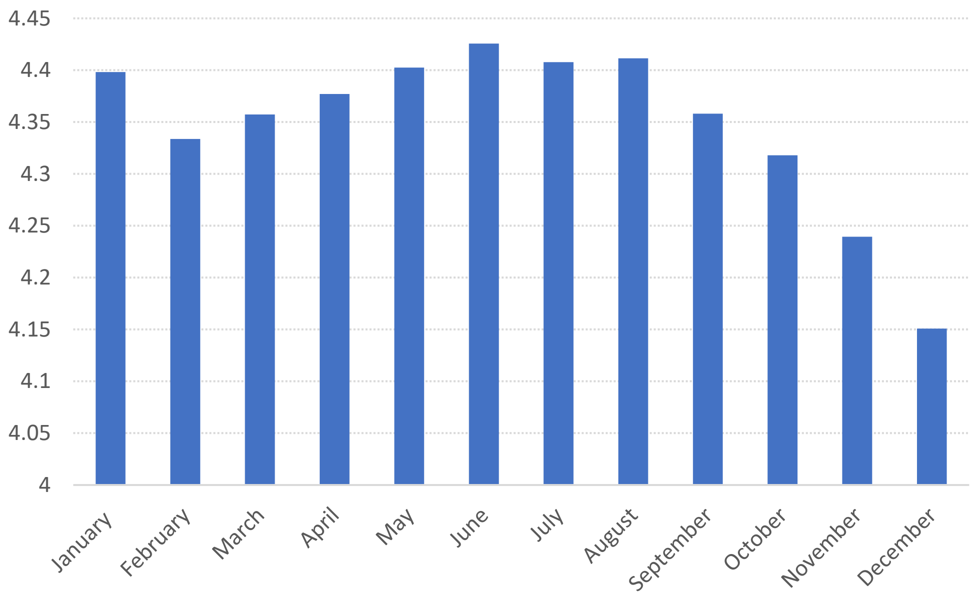


Figure 4: The average job search index for each month

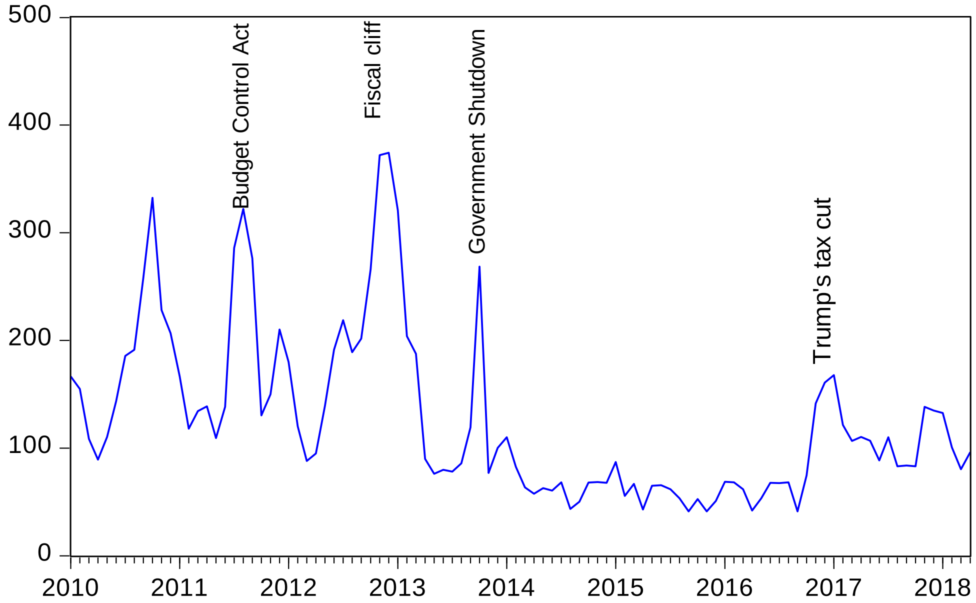
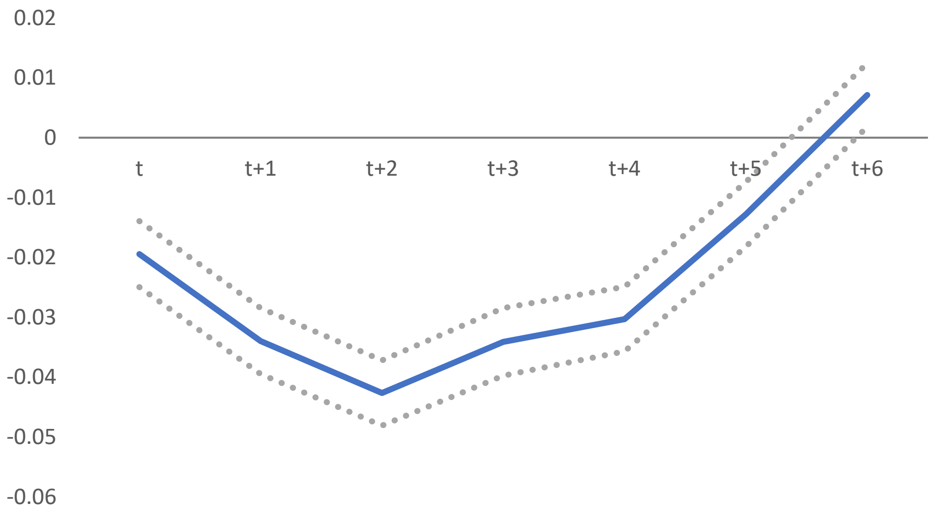
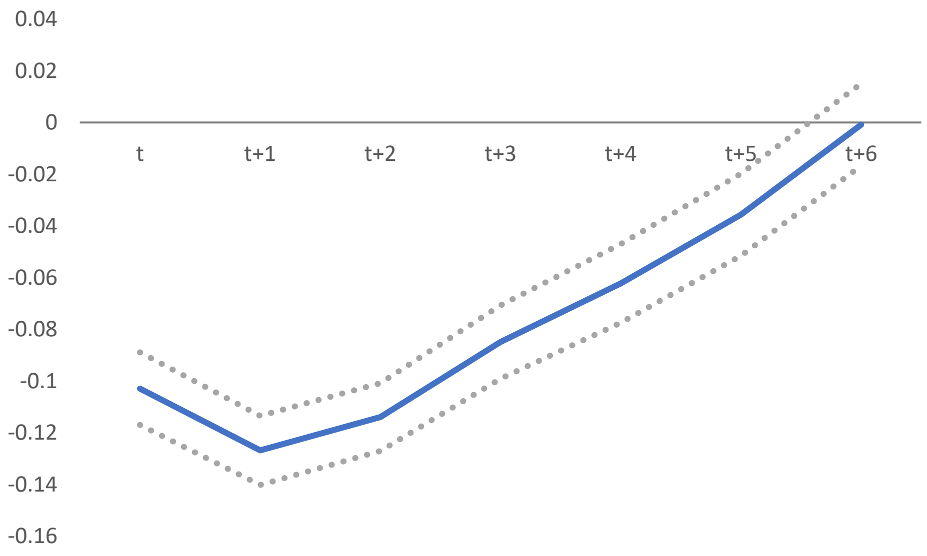


Figure 5. Fiscal policy uncertainty index



(A) Job search



(B) Job posting

Figure 6. 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, GSP growth rate, state unemployment rate, squared unemployment rate, and state labour force participation rate. The baseline specification is used and we control for state 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)	(5)	(6)	(7)	(8)	(9)	(10)
FPU	-0.284***	-0.285***	-0.281***	-0.106***	-0.103***	-0.022***	-0.022***	-0.031***	-0.019***	-0.019***
	(0.025)	(0.006)	(0.006)	(0.007)	(0.007)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
GSP growth				-0.239	-0.249				0.374***	0.375**
				(0.345)	(0.339)				(0.119)	(0.119)
Labour Force				-0.041***	-0.046***				0.010***	0.011
				(0.005)	(0.005)				(0.002)	(0.002)
Unemployment				-0.086***	-0.178				0.026***	0.041***
				(0.003)	(0.011)				(0.001)	(0.002)
Squared Unemployment					0.007***					-0.001***
					(0.001)					(0.0003)
Constant	7.764***	7.764***	7.782***	10.174***	10.759***	4.245***	4.245***	4.302***	3.736***	3.640***
	(0.116)	(0.029)	(0.045)	(0.307)	(0.318)	(0.015)	(0.014)	(0.013)	(0.133)	(0.142)
Month dummies	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
State FE	No	Yes	Yes	Yes	Yes	No	Yes	Yes	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	0.237	0.241	0.444	0.454	0.009	0.180	0.318	0.434	0.435

Table 2. 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, GSP growth rate, 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 state 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	-0.049***	-0.156***	-0.026***	-0.064***
	(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
Wald test	23.30***		40.13***	
Observations	3,621	1,428	3,621	1,428
Adj. R-squared	0.349	0.289	0.288	0.393

Table 3. 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, GSP growth rate, state unemployment rate, squared unemployment rate, and state labour force participation rate. The baseline specification is used and we control for state 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	-0.096***	-0.083***	-0.030***	0.010
	(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
Wald Test	22.9***		100.44***	
Observations	2,958	2,091	2,958	2,091
Adj. R-squared	0.342	0.426	0.355	0.131

Table 4. 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 GSP growth rate, state unemployment rate, squared unemployment rate, and state labour force participation rate. The baseline specification is used and we control for state 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	-0.040*** (0.007)		0.142*** (0.011)	-0.013*** (0.002)		-0.003 (0.004)
Tax		-0.121*** (0.007)	-0.296*** (0.016)		-0.020*** (0.003)	-0.016** (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	0.433	0.452	0.472	0.313	0.320	0.324

Table 5. 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. PCA refers to principal component analysis. Appendix A lists the geographical classifications.

	Job Search		Job Posting	
	Correlation	Variance Explained by First Factor—PCA	Correlation	Variance Explained by First Factor—PCA
All States	0.659	0.711	0.649	0.680
New England	0.574	0.691	0.467	0.578
Middle Atlantic	0.591	0.737	0.845	0.897
East North Central	0.906	0.925	0.849	0.879
West North Central	0.731	0.776	0.620	0.688
South Atlantic	0.583	0.739	0.713	0.760
East South Central	0.908	0.932	0.819	0.865
West South Central	0.770	0.828	0.737	0.803
Mountain	0.714	0.754	0.675	0.719
Pacific	0.379	0.536	0.359	0.558

Table 6. Estimates for each state

This table shows the estimated coefficients of FPU for each state. The number of observations is 99 from Feb 2010 to Apr 2018. Baseline regression is performed. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

		Job Posting		Job Search	
Region	State	Beta	Std	Beta	Std
East South Central	Alabama	-0.194**	0.073	-0.049**	0.022
East North Central	Illinois	-0.133***	0.042	-0.044***	0.014
East North Central	Indiana	-0.047	0.036	-0.051**	0.02
East North Central	Michigan	-0.045	0.044	-0.044***	0.014
East North Central	Ohio	-0.116**	0.048	-0.032*	0.018
East North Central	Wisconsin	-0.024	0.045	-0.030**	0.014
East South Central	Kentucky	-0.154**	0.074	-0.027	0.026
East South Central	Mississippi	-0.149***	0.046	-0.063***	0.023
East South Central	Tennessee	-0.074	0.056	-0.018	0.023
Middle Atlantic	New Jersey	-0.063**	0.03	-0.064**	0.027
Middle Atlantic	New York	-0.064	0.041	-0.007	0.025
Middle Atlantic	Pennsylvania	0.008	0.042	-0.034*	0.018
Mountain	Arizona	-0.123**	0.05	-0.049**	0.019
Mountain	Colorado	-0.066	0.041	-0.049***	0.016
Mountain	Idaho	0.021	0.044	-0.022	0.014
Mountain	Montana	-0.181***	0.065	-0.028**	0.014
Mountain	Nevada	0.004	0.041	-0.027*	0.016
Mountain	New Mexico	-0.123***	0.037	-0.02	0.017
Mountain	Utah	-0.122**	0.058	-0.014	0.017
Mountain	Wyoming	-0.141***	0.043	-0.001	0.018
New England	Connecticut	-0.066	0.051	-0.064**	0.026
New England	Maine	-0.077	0.086	-0.021	0.016
New England	Massachusetts	-0.136***	0.044	-0.048***	0.014
New England	New Hampshire	-0.036	0.043	-0.037*	0.02
New England	Rhode Island	-0.075	0.086	-0.007	0.02
New England	Vermont	-0.04	0.073	-0.035	0.026
Pacific	Alaska	-0.069	0.062	-0.004	0.014
Pacific	California	-0.090***	0.031	-0.012	0.019
Pacific	Hawaii	0.028	0.066	-0.034**	0.017
Pacific	Oregon	-0.097	0.061	0.036	0.033
Pacific	Washington	-0.112***	0.042	-0.029**	0.014
South Atlantic	Delaware	0.009	0.048	-0.036**	0.018
South Atlantic	District of Columbia	-0.126***	0.043	0.018	0.021
South Atlantic	Florida	-0.091**	0.044	-0.046**	0.02
South Atlantic	Georgia	-0.07	0.05	-0.021	0.026
South Atlantic	Maryland	0.024	0.045	-0.035*	0.02
South Atlantic	North Carolina	-0.080**	0.035	-0.042**	0.018
South Atlantic	South Carolina	-0.089**	0.041	-0.032	0.02
South Atlantic	Virginia	0.028	0.041	0.009	0.038
South Atlantic	West Virginia	0.004	0.073	-0.046**	0.021
West North Central	Iowa	-0.129**	0.063	-0.041**	0.019
West North Central	Kansas	-0.140**	0.059	-0.021	0.025
West North Central	Minnesota	-0.076	0.055	-0.041***	0.012
West North Central	Missouri	-0.002	0.05	-0.024*	0.014
West North Central	Nebraska	-0.180***	0.049	-0.017	0.018
West North Central	North Dakota	-0.078	0.058	-0.043***	0.016
West North Central	South Dakota	0.066	0.099	-0.031*	0.016
West South Central	Arkansas	-0.166***	0.061	-0.027	0.023
West South Central	Louisiana	-0.209***	0.058	-0.059**	0.025
West South Central	Oklahoma	-0.007	0.049	-0.003	0.024
West South Central	Texas	-0.069**	0.035	-0.038	0.023

Table 7. Determinants of variations in FPU's coefficients

This table shows the determinants of FPU coefficients. Possible factors include state manufacturing employment share, state mining employment share, labour freedom score, and average income per capita. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Job posting	Job search
Manufacturing	-0.561***	-0.036
	(0.187)	(0.072)
Mining	-0.595***	0.106*
	(0.196)	(0.058)
Labor Freedom	0.019	-0.003
	(0.052)	(0.019)
Avg income per capita	0.013*	0.003
	(0.007)	(0.019)
Observations	50	50
R-squared	0.123	0.063

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 state 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***	-0.367***		
	(0.010)	(0.010)	(0.011)	(0.011)		
Job search		0.689***		0.676***		-1.205***
		(0.033)		(0.031)		(0.068)
FPU			0.134***	0.130***	-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	0.705	0.933	0.723	0.975	0.305	0.368

Table 9. Endogeneity: Consider economic uncertainty

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, GSP growth rate, state unemployment rate, squared unemployment rate, and state labour force participation rate. The baseline specification is used and we control for state fixed effects. Panel A reports the results using residual of regressing U.S. FPU on Canadian economic policy uncertainty. Panel B reports the results after controlling for one-month ahead macroeconomic uncertainty (MU), and financial uncertainty (FU) indices by Jurado et al. (2015), and general economic policy uncertainty (EPU) from Baker et al. (2016). 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)	-0.130***	-0.017***
	(0.009)	(0.003)
State FE	Yes	Yes
Other controls	Yes	Yes
Constant	Yes	Yes
Observations	5,049	5,049
Adj. R-squared	0.942	0.433

Panel B: Adding macroeconomic and financial uncertainties

	(1)	(2)
	Job postings	Job search
FPU	-0.230***	-0.014***
	(0.011)	(0.003)
EPU	0.258***	0.034***
	(0.017)	(0.006)
MU	-1.128***	-0.311***
	(0.070)	(0.027)
FU	0.174***	0.255***
	(0.044)	(0.019)
Other controls	Yes	Yes
Constant	Yes	Yes
State FE	Yes	Yes
Observations	5,049	5,049
Adj. R-squared	0.947	0.465

Table 10. Endogeneity: Instrumental variable analysis

This table reports the first stage of two-stage least square regression results where the measure of national security uncertainty is the instrument. The dependent variable of second stage regressions is state's job search index or number of job postings. Independent variables include fiscal policy uncertainty (FPU) index, GSP growth rate, state unemployment rate, squared unemployment rate, and state labour force participation rate. The baseline specification is used and we control for state fixed effects. Panel A reports the results using residual of regressing U.S. FPU on Canadian economic policy uncertainty. Panel B reports the results after controlling for one-month ahead macroeconomic uncertainty (MU), and financial uncertainty (FU) indices by Jurado et al. (2015). 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)
	First Stage	Second stage for job postings	Second Stage for job search
National Security	0.748*** (0.069)		
Fitted FPU		-0.193*** (0.031)	-0.162*** (0.017)
State FE	Yes	Yes	Yes
Other controls	Yes	Yes	Yes
Constant	Yes	Yes	Yes
Observations	99	5,049	5,049
Adj. R-squared	0.693	0.942	0.436
F-test of exclude instrument	118.74***		

Table 11. Endogeneity: Using election dummy

The dependent variable of the regressions is state's log job postings or log of job search index. Independent variables include presidential election dummy proxy for FPU, GSP growth rate, state unemployment rate, squared unemployment rate, and state labour force participation rate. The baseline specification is used and we control for state 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)
	Job Postings	Job search
Presidential elections	-0.056***	-0.066***
	(0.015)	(0.006)
State FE	Yes	Yes
Other controls	Yes	Yes
Constant	Yes	Yes
Observations	5,049	5,049
Adj. R-squared	0.940	0.436

Table 12. 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, GSP growth rate, state unemployment rate, squared unemployment rate, and state labour force participation rate. All columns include realised equity volatility, which is calculated as 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 state 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	-0.104***	-0.113***	-0.022***	-0.023***
	(0.007)	(0.009)	(0.003)	(0.004)
RV_t	4.643***		6.238***	
	(1.402)		(0.523)	
RV_{t-1}	-0.655		0.363	
	(1.504)		(0.569)	
Fiscal Policy VIX_t		0.019*		0.004***
		(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	0.942	0.942	0.449	0.435

Table 13. Robustness checks: Alternative measure of FPU

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 measure of fiscal policy uncertainty (FPU), GSP growth rate, state unemployment rate, squared unemployment rate, and state labour force participation rate. Tax code expiration is used to tax policy uncertainty, government spending uncertainty is from the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters. The baseline specification is used and we control for state 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. Tax policy uncertainty is proxy by the expiration of tax code. Government spending uncertainty is proxied by survey dispersion related to federal, state, local government consumption. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Job postings			Job search		
Tax	-0.015***		-0.016***	-0.003**		-0.003**
	(0.003)		(0.003)	(0.001)		(0.001)
Government spending		-0.243***	-0.245***		-0.008	-0.009
		(0.017)	(0.017)		(0.008)	(0.008)
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	0.942	0.943	0.944	0.426	0.426	0.431

Table 14. 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, GSP growth rate, state unemployment rate, squared unemployment rate, and state labour force participation rate. The baseline specification is used and we control for state 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	-0.103***	-0.110***	-0.019***	-0.018***
	(0.007)	(0.007)	(0.003)	(0.003)
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	0.942	0.942	0.435	0.434

Panel B: Detrending

	(1)	(2)
	Cyclical Job posting	Cyclical Job search
FPU	-0.122***	-0.020***
	(0.010)	(0.003)
Other controls	Yes	Yes
Constant	Yes	Yes
State FE	Yes	Yes
Observations	3,672	3,672
Adj. R-squared	0.157	0.239

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	-0.103***	-0.098***	-0.019**	-0.019***
	(0.031)	(0.011)	(0.009)	(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	0.942	0.942	0.435	0.435