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Why Still Vacant? Different Dynamics between Vacancy and Recruiting Intensity from the Impact of Uncertainty Shocks

불확실성 충격으로부터의 채용공고와 채용강도의 상이한 반응과 그 동학에 관한 연구

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Abstract

Why Still Vacant? Different Dynamics between Vacancy and Recruiting Intensity from the Impact of Uncertainty Shocks

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This paper addresses a puzzling observation of the sluggish recovery pace of recruiting intensity compared to vacancies after the Great Recession. I hypothesize two economic elements to explain the observation: (i) the realistic features of the recruiting process and (ii) the impact of uncertainty shocks. By postulating the recruiting process as a sequential procedure of vacancy creation as a plan and recruiting intensity as an action, hence, positing vacancy as a state variable, this paper allows for reactions from the impact of the uncertainty shocks which differ from conventional reactions. Using vector autoregression, I show that there are statistically significant responses of recruiting intensity from the uncertainty shock while not for vacancy. Also, by constructing a dynamic stochastic general equilibrium model with a generalized search and matching framework,

I show that there are larger negative responses in recruiting intensity compared to vacancy from the impact of second-order shocks.
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Keywords: Vacancy, Recruiting Intensity, Uncertainty Shock, Plan and Action, Sluggish Recovery
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1 Introduction

Since the Great Recession, many scholars have given attention to the sluggish recovery of employment in the United States. In light of the standard Pissarides-type search and matching framework, the phenomenon can be represented as a decline in matching efficiency. As Figure 1 shows, the aggregate matching efficiency has drastically declined since the Great Recession, and it has not recovered yet to the pre-crisis level.[1]

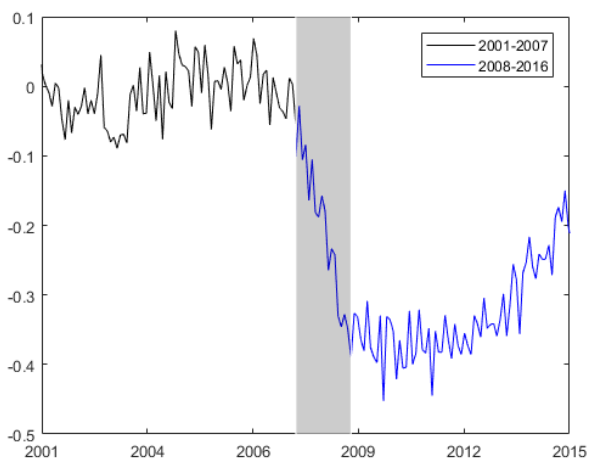


Figure 1: Aggregate matching efficiency: Jan.2001-Nov.2016

To understand the fundamental causes of huge drops and sluggish recovery in matching efficiency, many scholars have researched both the labor supply and demand. In the case of the labor supply, several authors[2] have

[1]By utilizing the hiring, unemployment and vacancy data from the BLS and JOLTS, I derive the log aggregate matching efficiency from the standard search matching equation $h_t = z_t u_t^{\alpha} v_t^{1-\alpha} \Leftrightarrow log(z_t) = log(h_t) - (\alpha log(u_t) + (1-\alpha) log(v_t))$, where $\alpha = 1/2$ by following Lin (2014)[1]. Also the shaded area indicates the Great Recession period from NBER, i.e., Dec.2007-Jun.2009.

[2]See Hall and Schulhofer-Wohl (2013)[2] and Mukoyama, Patterson, and Şahin (2013)[3]

tried to explain the impact of the worker side in terms of the composition of workers and workers' job search efforts. Hornstein and Kudlyak (2016)[4], however, showed that the decline in aggregate matching efficiency is still unexplained, although they controlled the composition effect and the job search efforts. Therefore, according to them, the labor supply has a minimal impact on the aggregate matching efficiency around the Great Recession.

From the perspective of labor demand side, Davis, Faberman, and Haltiwanger (2013)[5] (hereafter, DFH) found a way to explain the drop in aggregate matching efficiency by introducing "recruiting intensity" which means a firm's effort to cover its vacancies. By extending this concept, some papers have shown the pro-cyclity of recruiting intensity with alternative specifications[3], and these attempts have enhanced our understanding of the recruiting intensity reaction from the real and financial first-order shocks.

However, there is a remaining issue regarding the need to fully understand the dynamics of the labor market after the Great Recession. To get a sense of this issue, I quote recent "A review of labor market conditions" on the Federal Reserve Economic Data (FRED) blog:

> "Since the 2007-09 recession, vacancy durations have surpassed pre-recession levels, reaching a series high of 29.6 business days per vacancy in April 2016. ***The recruiting intensity index is close to its pre-recession level, but has not increased as quickly as vacancy durations***."

To see this data fact, I come up with Figure 2 by plotting the vacancy rate

[3]See Kaas and Kircher (2015)[6] and Gavazza, Mongey, and Violante (2016)[7]

and recruiting intensity using the JOLTS and DFS, respectively[4]. Clearly, the recovery pace of vacancy rate is much faster than that of recruiting intensity. The rate of vacancy has been recovered to its pre-recession level, but recruiting intensity has not.

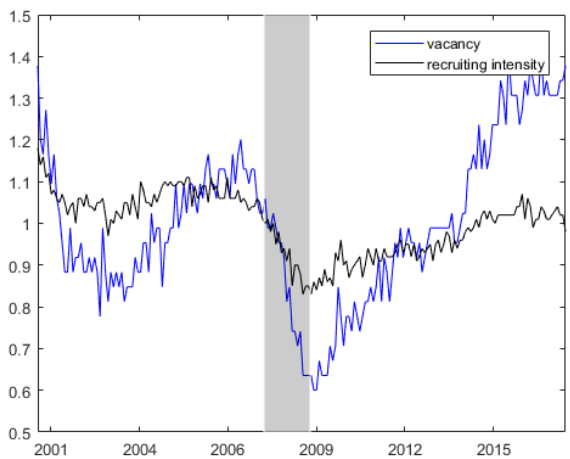


Figure 2: Vacancy and recruiting intensity dynamics: Jan.2001-Apr.2017

To explain the sluggish recovery of recruiting intensity, I adopt a real-world recruiting process. A firm creates vacancies for its next period of hiring, and in the next period, it attempts to decide whether it fully covers its created vacancies according to the market condition in the period. That is, a firm attempts to use vacancies as an option for the future hiring, and to utilize recruiting intensity as the determinant of hiring. Therefore, when a firm makes a decision about vacancy and recruiting intensity, it may differently react to the future first- and second-order shocks. For example, if a firm expects the future demand to increase, it increases its vacancies, however it

[4]I normalize the vacancy rate by matching the mean value with that of the recruiting intensity to see the pace of dynamics

does not need to significantly change its recruiting intensity because it can control future hiring in the next period using recruiting intensity in the next period. In contrast, if a firm realizes future demand uncertainty is high, it decreases its recruiting intensity due to the possibility of labor adjustment, but does not need to greatly decrease its vacancies, as a firm will determine its eventual hiring in the future after the market uncertainty is resolved.

To incorporate the above idea, I use vacancy as a state variable in a DSGE model. By adjusting Justiniano and Primiceri (2008) (hereafter, JP)[14], I estimate structural parameters. Although a further robustness check is still needed for estimation, the impact of uncertainty shocks generate a greater response to recruiting intensity compared to the vacancy rate. However, it fails to reproduce my hypothesis in which first-order productivity shock affects vacancies more than recruiting intensity. Therefore further investigation will be needed to tackle this issue.

This paper is structured as follows. I investigate a relationship between a firm's labor inputs (vacancy and recruiting intensity) and first- and second-order shocks in section 2. After observing raw data and brief correlations, I conduct vector autoregression (VAR) analysis to see dynamic interactions between uncertainty and vacancy and recruiting intensity. In section 3, I modify the model of Lin (2014)[1] by incorporating the generalized search and matching model. Then I calibrate and estimate the model parameters by adjusting JP[14] in section 4. In section 5, I compare real data and model-generated data, and investigate the impulse response function from the first- and second-order shock. I make concluding remarks in section 6.

2 Empirical Evidence

2.1 Data Observation

Before constructing a theoretical model, it is important to observe the exisiting data on the correlation between first- and second- moments of shock, vacancy, and recruiting intensity. As Baker, Bloom and Davis (2016)[8] controlled the S&P500 index for the first-moment shock since the stock market mainly reacts to the bad news, I also posit the S&P500 index as a representative of first-moment shock. In addition, I try to observe the impact of uncertainty shocks by utilizing Economic Policy Uncertainty (EPU) introduced by Baker, Bloom and Davis (2016)[8]. I normalize all the variables to match their means to 10 for the purpose of comparison.

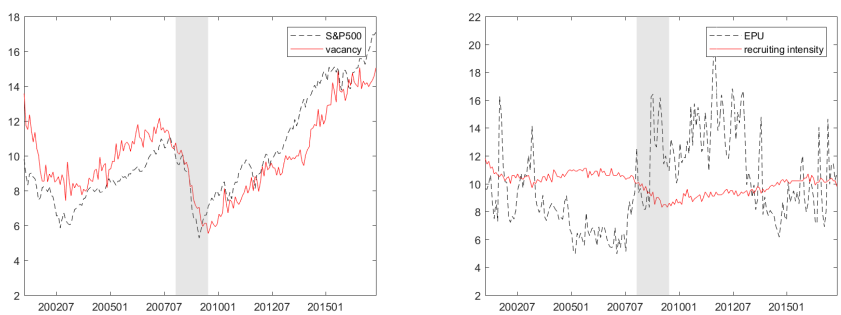


Figure 3: Vacancy and recruiting intensity with first- and second- moment shocks

The left panel of Figure 3 shows that the S&P500 index, which I choose as a representative of first-moment shock exhibits strong co-movement with vacancies posted. The right panel shows that the EPU index, a representative of second-moment shock, negatively co-moves with recruiting intensity. However, it is insufficient to observe only graphs, so I calculate correlations

between the moment variables and vacancy and recruiting intensity in Table 1, where v and a denote vacancy and recruiting intensity, respectively.

Using Steiger (1980)'s[9] method to test the difference in correlation coefficients, I tested the difference in correlation between vacancy and recruiting intensity for each moment of shock. With the 196 observations of each time series and the correlation between vacancy and recruiting intensity, 0.5431, the null hypothesis in which there is no difference between correlations is rejected at a 1 percent significance level for both the S&P500 index and EPU index. That is, the first-moment shock positively co-moves much stronger with vacancy compared to recruiting intensity while the second-moment shock negatively co-moves much stronger with recruiting intensity compared to vacancy. With these observations, I suggest that it is important to understand how each moment of shock interacts with vacancy and recruiting intensity to explain different dynamics after the Great Recession.

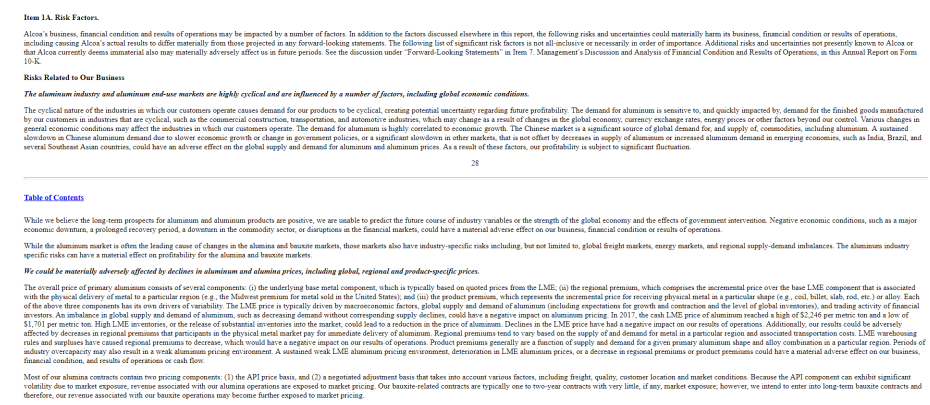
Table 1: Correlation matrix

	v	a
S&P500	0.8309	0.1202
EPU	-0.3901	-0.6508

Drawing the above observation requires a close examination about a representative measure of uncertainty which firms perceive as their business uncertainty. I use the Economic Policy Uncertainty to show the much stronger negative correlation with recruiting intensity than vacancy. There are several uncertainty measures in previous literature such as stock market volatility, VIX index, firm growth rate dispersion, and so on. However, it is hard to know how really firms perceive their business uncertainty through listed

measure. In response to the need of understanding how real world firms recognize business uncertainty, Bachmann, Carstensen, and Schneider [10] are conducting extensive survey about German firms' uncertainty and ambiguity. However, this project is still going on, so I couldn't utility their data.

Baker, Bloom, and Davis (2013) [**?**] tries to show that the economic policy uncertainty can be a main source when firms perceive about the future demand uncertainty. They investigated *risk factors* section of 10-K (annual report of a firm) of U.S. listed firms. To pull-out meaningful implications from this investigation, they use the fact that firms tend to put an important risk factor first when ordering their risk factors. Therefore, by counting the relative rank of economic policy related risk factors, they show that the economic policy related risk factors are located in rank 1.5 out 10, indicating relative strong importance of economic policy uncertainty to firms.



Item 1A. Risk Factors.

Alcoa's business, financial condition and results of operations may be impacted by a number of factors. In addition to the factors discussed elsewhere in this report, the following risks and uncertainties could materially harm its business, financial condition or results of operations, including causing Alcoa's actual results to differ materially from those projected in any forward-looking statements. The following list of significant risk factors is not all-inclusive or necessarily in order of importance. Additional risks and uncertainties not presently known to Alcoa or that Alcoa currently deems immaterial also may materially adversely affect us in future periods. See the discussion under "Forward-Looking Statements" in Item 7. Management's Discussion and Analysis of Financial Condition and Results of Operations, in this Annual Report on Form 10-K.

Risks Related to Our Business

The aluminum industry and aluminum end-use markets are highly cyclical and are influenced by a number of factors, including global economic conditions.

The cyclical nature of the industries in which our customers operate causes demand for our products to be cyclical, creating potential uncertainty regarding future profitability. The demand for aluminum is sensitive to, and quickly impacted by, demand for the finished goods manufactured by our customers in industries that are cyclical, such as the commercial construction, transportation, and automotive industries, which may change as a result of changes in the global economy, currency exchange rates, energy prices or other factors beyond our control. Various changes in general economic conditions may affect the industries in which our customers operate. The demand for aluminum is highly correlated to economic growth. The Chinese market is a significant source of global demand for, and supply of, commodities, including aluminum. A sustained slowdown in Chinese aluminum demand due to slower economic growth or change in government policies, or a significant slowdown in other markets, that is not offset by decreases in supply of aluminum or increased aluminum demand in emerging economies, such as India, Brazil, and several Southeast Asian countries, could have an adverse effect on the global supply and demand for aluminum and aluminum prices. As a result of these factors, our profitability is subject to significant fluctuation.

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While we believe the long-term prospects for aluminum and aluminum products are positive, we are unable to predict the future course of industry variables or the strength of the global economy and the effects of government intervention. Negative economic conditions, such as a major economic downturn, a prolonged recovery period, a downturn in the commodity sector, or disruptions in the financial markets, could have a material adverse effect on our business, financial condition or results of operations.

While the aluminum market is often the leading cause of changes in the alumina and bauxite markets, those markets also have industry-specific risks including, but not limited to, global freight markets, energy markets, and regional supply-demand imbalances. The aluminum industry specific risks can have a material effect on profitability for the alumina and bauxite markets.

We could be materially adversely affected by declines in aluminum and alumina prices, including global, regional and product-specific prices.

The overall price of primary aluminum consists of several components: (i) the underlying base metal component, which is typically based on quoted prices from the LME; (ii) the regional premium, which comprises the incremental price over the base LME component that is associated with the physical delivery of metal to a particular region (e.g., the Midwest premium for metal sold in the United States); and (iii) the product premium, which represents the incremental price for receiving physical metal in a particular shape (e.g., coil, billet, slab, rod, etc.) or alloy. Each of the above three components has its own drivers of variability. The LME price is typically driven by macroeconomic factors, global supply and demand of aluminum (including expectations for growth and contraction and the level of global inventories), and trading activity of financial investors. An imbalance in global supply and demand of aluminum, such as decreasing demand without corresponding supply declines, could have a negative impact on aluminum pricing. In 2017, the cash LME price of aluminum reached a high of $2,246 per metric ton and a low of $1,701 per metric ton. High LME inventories, or the release of substantial inventories into the market, could lead to a reduction in the price of aluminum. Declines in the LME price have had a negative impact on our results of operations. Additionally, our results could be adversely affected by decreases in regional premiums that participants in the physical metal market pay for immediate delivery of aluminum. Regional premiums tend to vary based on the supply of and demand for metal in a particular region and associated transportation costs. LME warehousing rules and surpluses have caused regional premiums to decrease, which would have a negative impact on our results of operations. Product premiums generally are a function of supply and demand for a given primary aluminum shape and alloy combination in a particular region. Periods of industry overcapacity may also result in a weak aluminum pricing environment. A sustained weak LME aluminum pricing environment, deterioration in LME aluminum prices, or a decrease in regional premiums or product premiums could have a material adverse effect on our business, financial condition, and results of operations or cash flow.

Most of our alumina contracts contain two pricing components: (1) the API price basis, and (2) a negotiated adjustment basis that takes into account various factors, including freight, quality, customer location and market conditions. Because the API component can exhibit significant volatility due to market exposure, revenue associated with our alumina operations are exposed to market pricing. Our bauxite-related contracts are typically one to two-year contracts with very little, if any, market exposure; however, we intend to enter into long-term bauxite contracts and therefore, our revenue associated with our bauxite operations may become further exposed to market pricing.

Changes to LME policies could cause aluminum prices to decrease.

Figure 4: An example of risk factors section in Alcoa's 10-K

2.2 VAR Analysis and Economic Hypothesis

While the brief correlation analysis makes us to guess there would be different reaction of vacancy and recruiting intensity from each of first and second order shocks, I explicitly analyze interactions among those variables using VAR analysis. Using Structural VAR analysis we can see a dynamic interaction between the variables by identifying structural shocks.

After Bloom (2009)[21], there have been numerous literature which analyze empirical consequences of the uncertainty shocks. I, however, want to focus on the response of vacancy and recruiting intensity from the first and second order variables' shock. In Baker, Bloom and Davis (2016)[8], they analyze the impact of uncertainty shocks to industrial production and employment using EPU which they construct. They show that there are statistically significant negative response of both variables from the uncertainty shock.

I utilize their VAR specification by altering employment to vacancy and recruiting intensity. The baseline specification of my VAR analysis as below:

$$Y_t = A + \sum_{j=1}^{lags} B_j Y_{t-j} + C\epsilon_t, \epsilon_t \sim N(0, I), \tag{1}$$

where $Y_t = (\sigma_t, log(s_t), r_t, log(v_t), log(a_t), log(ip_t))$ and ϵ_t is a vector of structural shocks (σ_t: Economic Policy Uncertainty index, s_t: S&P 500, r_t: Federal Fund Rate, v_t: vacancy level, a_t: recruiting intensity level, and ip_t: industrial production index).[5] VAR analysis for those variables is conducted us-

[5]Data sources: 1. Economic Policy Uncertainty from http://policyuncertainty.com in which the index is constructed by the method of Baker, Bloom, and Davis (2016)[8]; 2. S&P500 from yahoo finance; 3. Federal Fund Rate from FRED; 4. Vacancy from Job Opening and Labor Turnover Survey which is seasonally adjusted; 5. Recruiting Intensity from DHI monthly recruiting intensity index; 6. Industrial production from FRED.

ing monthly data from January, 2001 to February, 2018. I conduct standard Cholesky Decomposition to identify structural shocks by above Y_t ordering. Note that I put vacancy over recruiting intensity first by reflecting my hypothesis to be explained soon. I set the lag as three for the baseline analysis.

Of course, there might be a problem using above specification in which I use time-series level data. As you may know, those time-series data may have unit root that make hard to do a traditional statistical test of impulse response function. However, many recent empirical time-series analyses do not care that much about non-stationarity because a power of a unit root test (i.e., augmented Dickie-Fuller test) is too low to reject the null hypothesis of having a unit root. Although Baker, Bloom, and Davis (2009)[8] does not specify the reason why they use time series level data which possibly possess a unit root, I guess they might justify their specification by arguing a low power of a unit root test.

After admitting the above model, I want to care one more thing. Since the data I gathered includes Great Recession (i.e., 2008 Global Financial Crisis) period which may be seen as very extraordinary economic situation, I need to control those period as putting exogenous variable to (1). Controlling the Great Recession period allows us to see clear picture of dynamic interaction among specified variables.[6] To control the Great Recession period, I put a dummy variable which has a value one for the Great Recession period and zero otherwise. Let the Great Recession dummy X_t, then I estimate the following vector autoregression with an exogenous variable (VAR-X) model in

[6] I use the NBER Great Recession period definition: December, 2007 - June, 2009.

a same way of estimating (1).

$$Y_t = A + \sum_{j=1}^{lags} B_j Y_{t-j} + EX_t + C\epsilon_t, \epsilon_t \sim N(0, I) \tag{2}$$

By estimating the above structural VAR models (1) and (2), I draw impulse response functions (IRF) as shown in Figure 5. I estimated the standard errors by using Kilian (1998)'s[18] bootstrap-after-bootstrap method. From this figure I can see that the uncertainty shocks affect recruiting intensity in a statistically significant way while do not vacancy. This result is much more significant when I control the Great Recession period as an exogenous dummy variable.

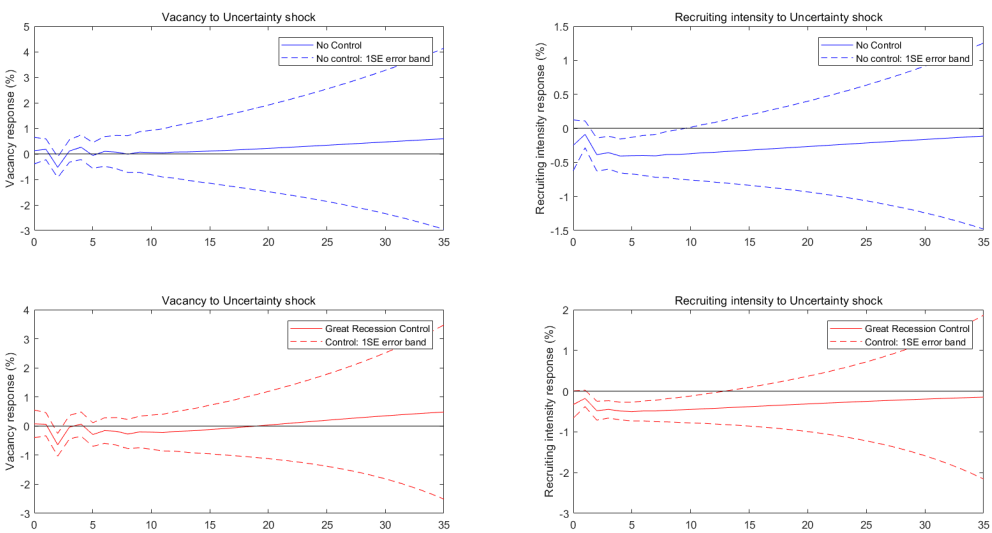

Figure 5: IRFs under the impact of the uncertainty shocks

To see clear difference in reactions of vacancy and recruiting intensity from the first and second order shocks, I also depict their reactions from the impact of S&P shocks as Figure 6. Without controlling the Great Recession

period, responses of vacancy and recruiting intensity from the S&P shocks seem statistically significant. Controlling the Great Recession period, however, makes significant difference in their reactions. When we control for the Great Recession period, vacancy exhibits significant reactions while recruiting intensity does not. Further robustness checks are done in Appendix.

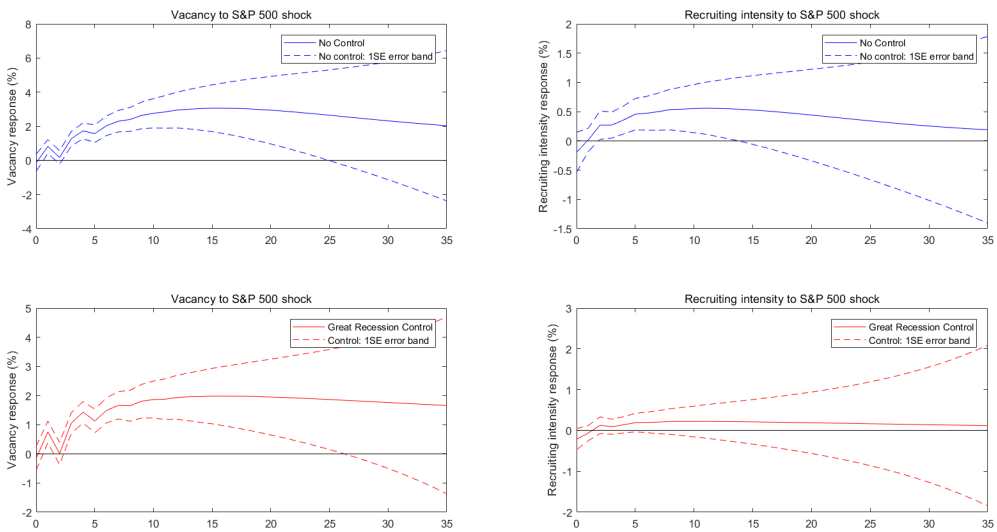

Figure 6: IRFs under the impact of the first-order S&P shocks

To explain the different reactions of each variable from the different order of shocks, I raise the following hypothesis which reflects the real-world recruiting process: a firm does not gauge current vacancies and determine recruiting intensity at the same time, but plans on the vacancies for the next period and then covers the created vacancies through its recruiting intensity

after the market uncertainty of the next period is resolved.[7] In the models[8] from the previous researches which deal with vacancies and recruiting intensity, a firm determines its vacancies and recruiting intensity at the same time. However, it is natural to imagine that a firm creates vacancies as a tool for planning the next period's hiring, and a firm decides in the next period whether it covers the created vacancies through its recruiting intensity after resolving the demand uncertainty.

This hypothesis is consistent with the observed empirical evidence in the following ways: (i) if the future demand (a first-order shock) is expected to increase, a firm attempts to increase vacancies while setting its recruiting intensity to match. Since the future hiring will be determined only after the next period's recruiting intensity is confirmed, that is current recruiting intensity does not react to the future demand shocks; (ii) if the future demand uncertainty (a second-order shock) is expected to increase, a firm tries to adjust its current recruiting intensity due to the labor adjustment cost; however, it does not control current vacancies because they are linked to the eventual hiring in the next period after the demand uncertainty is resolved.

3 Model

In section 3, I show the above hypothesized mechanism with a DSGE model. The model follows the specification of Lin (2014)[1], except some ad-

[7] In March 2016, SK announced that its ***target*** employment rate was 8,400 and actual employment was 8,100. Based on the initial recruitment plan only, SK has reduced its employment this year. Therefore, it is unlikely that the number of actual recruits will fall short of last year. SISA ON (a Korean magazine) 2017.02.03

[8] See Kaas and Kircher (2015)[6] and Gavazza, Mongey, and Violante (2016)[7]

ditional assumptions on labor market details, such as the generalized search-matching function and vacancy as a state variable. In the model, there are three kinds of economic entities: a representative household, a representative firm, and the government. Although most of the papers dealing with recruiting intensity allow the heterogeneity of firms to see the relationship between firms' growth rates and business cycle, I abstract from the heterogeneity, as I aim to focus on the mechanism in which first- and second- order shocks propagate to vacancies and recruiting intensity. As I mentioned above, the model incorporates a realistic feature of the recruiting process by positing vacancy as a state variable, so that the impact of uncertainty shocks can differ for vacancy and recruiting intensity.

3.1 Frictional labor market

There is a unit measure of workers in the economy. The number of job seekers u_t consists of the remainder after separating ρ_0, the natural separation rate, the portion of employees in the previous period n_{t-1}. Then, the total number of jobless people in period t is

$$u_t = 1 - (1 - \rho_0) n_{t-1}. \tag{3}$$

Hiring in period t is the output based on matching between vacancies posted by the firms, recruiting intensity, and the number of job seekers in the economy. Utilizing the Cobb-Douglas matching function with recruiting intensity, the number of job matches (hiring) is determined as

$$h_t = h_0 u_t^{\alpha_h} (v_t a_t)^{1-\alpha_h}, \tag{4}$$

where a_t is recruiting intensity, v_t is vacancy, h_0 is the match scale parameter and α_h is the match elasticity of job seekers. Therefore, the aggregate employment is naturally determined as

$$n_t = (1 - \rho_0)n_{t-1} + h_t. \tag{5}$$

3.2 Households

The economy consists of a continuum of identical households. As mentioned in the introduction, the labor supply's impact on the sluggish recovery of employment is negligible. Therefore, I abstract from labor supply decision of households. Their employment statuses are solely determined by a firm's labor demand. Those who are employed receive wage income w_t and only those who are not have unemployment benefits b. From these components, households' Constant Relative Risk Aversion (CRRA) utility function can be written as:

$$E_t[\Sigma_{s=0}^{\infty}\beta^{t+s}\frac{c_{t+s}^{1-\gamma} - 1}{1-\gamma}], \tag{6}$$

where c_t denotes consumption, β denotes time discount factor, and γ denotes relative risk aversion parameter.

Further, households' utilize capital, k_t, for the purpose of either saving or borrowing. I also assume that households possess firms and they pay taxes to the government. Therefore households face the following budget constraint:

$$c_{t+s} + k_{t+s+1} \leq w_{t+s}n_{t+s} + b(1 - n_{t+s}) + (r_t + (1-\delta))k_{t+s} + \Pi_t - T_t, \forall s \tag{7}$$

where r_t denotes the real interest rate, δ the depreciation rate, Π_t the profit, and T_t the tax payment.

Households want to maximize their utility subject to the above budget constraint by choosing $\{c_{t+s}, k_{t+s+1}\}_{s=0}^{\infty}$.

3.3 Firms

Let's assume a representative firm where its production y_t is determined as follows:

$$y_t = z_t k_t^{\alpha} n_t^{1-\alpha}, \tag{8}$$

where z_t denotes the aggregate productivity in period t, k_t the physical capital in period t, n_t the employment in period t, and α the capital factor share.

The productivity z_t follows a first-order autoregressive as,

$$log(z_{t+1}) = \rho_z log(z_t) + \sigma_t \epsilon_{z,t+1}, \tag{9}$$

where ρ_z denotes the persistence parameter, and $\epsilon_{z,t+1} \sim i.i.d.N(0,1)$.

To gauge the impact of the uncertainty shocks, I design the following autoregressive process on the standard deviation, σ_t, of the productivity shock:

$$log(\sigma_t) = \rho_\sigma log(\sigma_{t-1}) + (1-\rho_\sigma) log(\bar{\sigma}) + \sigma_\sigma \epsilon_{\sigma,t}, \tag{10}$$

where ρ_σ denotes the persistence parameter, $\bar{\sigma}$ the steady state value of the standard deviation, σ_σ the standard deviation of volatility shock, and $\epsilon_{\sigma,t} \sim i.i.d.N(0,1)$. As shown in the productivity process, if an uncertainty shock

comes today, agents realize in the current period that the variance of the next period's productivity will increase.

Firm accumulates capital with investment I_t by following the law of motion of capital:

$$k_{t+1} = (1-\delta)k_t + I_t. \tag{11}$$

Equation 5 indicates the law of motion of employment. I also assume that the firm faces capital adjustment, $\frac{1}{2}K_c(\frac{I_t}{k_t})^2$, labor adjustment, $\frac{1}{2}K_n{h_t}^2$, vacancy creation, $\frac{1}{2}K_v{v_t}^2$, and recruiting intensity costs, $\frac{1}{2}K_a{a_t}^2$.[9]

Since I already assume that households possess the firm, the stochastic discount factor of the firm is same as of households. I incorporate a real-world recruiting process in which I hypothesize above by setting vacancy as a *state variable* in the firm's optimization problem. In period t, the representative firm chooses vacancy for the next period, v_{t+1}, recruiting intensity in period t, a_t, and investment in period t, I_t to maximize its value function by solving the following dynamics programming:

(12)

$$\begin{aligned} V_t(z_t, k_t, n_{t-1}, v_t, \sigma_t) = \max_{\{I_t, a_t, v_{t+1}\}} & \; y_t - w_t n_t - r_t k_t - \frac{1}{2}K_c(\frac{I_t}{k_t})^2 - \frac{1}{2}K_n{h_t}^2 \\ & - \frac{1}{2}K_v{v_t}^2 - \frac{1}{2}K_a{a_t}^2 + \beta E_t[\frac{\lambda_{t+1}}{\lambda_t}V_{t+1}(z_{t+1}, k_{t+1}, n_t, v_{t+1}, \sigma_{t+1})], \end{aligned}$$

[9] I utilize quadratic capital and labor adjustment cost to make the firm has an incentive to gradually adjust the inputs. Moreover, due to those adjustment costs, the firm reacts to the uncertainty shocks. See Merz and Yashiv (2007)[11] and Gertler, Sala, and Trigari (2008)[12] to see cases that utilize quadratic adjustment costs.

$s.t.$

$$y_t = z_t k_t^{\alpha} n_t^{1-\alpha},$$

$$n_t = (1-\rho_0)n_{t-1} + h_t,$$

$$h_t = h_0 u_t^{\alpha_h}(a_t v_t)^{1-\alpha_h},$$

$$log(z_{t+1}) = \rho_z log(z_t) + \sigma_t \epsilon_{z,t+1},$$

$$log(\sigma_t) = \rho_\sigma log(\sigma_{t-1}) + (1-\rho_\sigma)log(\bar{\sigma}) + \sigma_\sigma \epsilon_{\sigma,t},$$

$$k_{t+1} = (1-\delta)k_t + I_t,$$

where λ_t denotes Lagrange multiplier in the households problem, so $\beta\frac{\lambda_{t+1}}{\lambda_t}$ indicates the stochastic discount factor, and r_t the capital rental rate.

3.4 Wage dynamics

Assuming a frictional labor market within the search and matching framework, matching between job-seekers and vacancies posted generates a positive surplus; thus, the surplus should be allocated through wage negotiation.

To gauge the matching surplus, let's start to think of the value of job-seekers, U_t as follows:

$$U_t = b + \beta E_t[\frac{\lambda_{t+1}}{\lambda_t}(s_{t+1}W_{t+1} + (1-s_{t+1})U_{t+1})], \tag{13}$$

where W_t denotes the value of workers and s_t the job finding rate, that is $s_t = \frac{h_t}{u_t}$. In the equation, job-seekers value consists of the weighted average of worker's value and job-seekers value in the next period through a job-finding rate.

In the same logic, workers' value W_t follows as:

$$W_t = w_t + \beta E_t[\frac{\lambda_{t+1}}{\lambda_t}((1-\rho_0)W_{t+1} + \rho_0 U_{t+1})]. \tag{14}$$

Therefore, workers' net value by matching, S_t, is as follows:

$$S_t = W_t - U_t = w_t - b + \beta E_t[\frac{\lambda_{t+1}}{\lambda_t}((1-\rho_0 - s_{t+1})S_{t+1})]. \tag{15}$$

Firm's value by adding an additional worker is calculated as follows:

$$\mu_t = (1-\alpha)\frac{y_t}{n_t} - w_t + \beta E_t[\frac{\lambda_{t+1}}{\lambda_t}(1-\rho_0)\mu_{t+1}], \tag{16}$$

where $(1-\alpha)\frac{y_t}{n_t} - w_t$ means the marginal labor productivity over wage, and the latter term in the equation indicates continuation value. Therefore, total surplus $W_t + \mu_t$ is allocated by wage setting. Let's denote the upper bound of wage as w_t^u in which job-seekers take all the surplus with this wage, that is $\mu_t = 0$. Likewise, the lower bound of wage, w_t^l, in which the firm takes all the pie, can be calculated by $W_t = 0$. With simple algebra w_t^u and w_t^l show the following dynamics:

$$w_t^u = (1-\alpha)\frac{y_t}{n_t} + \beta E_t[\frac{\lambda_{t+1}}{\lambda_t}(1-\rho_0)(w_{t+1}^u - w_{t+1})], \tag{17}$$

$$w_t^l = b + \beta E_t[\frac{\lambda_{t+1}}{\lambda_t}(1-\rho_0)(1-\rho_0 - s_{t+1})(w_{t+1}^l - w_{t+1})]. \tag{18}$$

By utilizing these bounds, the standard Nash bargaining wage w_t^N can be calculated as:

$$w_t^N = \eta w_t^u + (1-\eta)w_t^l, \eta \in [0,1], \tag{19}$$

where η indicates workers' bargaining power.

To sidestep Shimer (2005)'s[13] unemployment volatility puzzle in which labor market data are much more volatile compared to the economics model, I allow ad-hoc wage rigidity to generate a more realistic employment response to productivity shocks. Wage w_t is shown as follows:

$$w_t = \tau w_{t-1} + (1-\tau) w_t^N, \tag{20}$$

where $\tau \in [0,1]$ indicates the degree of wage rigidity.

3.5 Government

The government in the model collects tax T_t from households to fund the total unemployment benefits $(1-n_t)b$:

$$T_t = (1-n_t)b. \tag{21}$$

Following Lin (2014) [1], I assume the unemployment benefits b follow:

$$b = \bar{b}(1-\alpha)\frac{\bar{y}}{\bar{n}}, \tag{22}$$

where $\bar{x}$ indicates a steady state of a variable x which means the unemployment benefits equal the steady state value of marginal labor productivity.

3.6 Resource Constraint

To close the model, the resource constraint is

$$y_t = c_t + \frac{1}{2}K_c(\frac{I_t}{k_t})^2 + \frac{1}{2}K_n {h_t}^2 + \frac{1}{2}K_v {v_t}^2 + \frac{1}{2}K_a {a_t}^2 + k_{t+1} - (1-\delta)k_t. \tag{23}$$

4 Calibration and Estimation Strategy

In the model, there are 18 parameters to be calibrated or estimated as follows:

$$\{\alpha, \alpha_h, \beta, \gamma, \delta, h_0, \rho_0, K_c, K_n, K_v, K_a, \eta, \tau, \bar{b}, \rho_z, \rho_\sigma, \sigma_\sigma, \bar{\sigma}\}.$$

I calibrate some of them based on the standard business cycle and macro-labor literature and estimate the rest utilizing JP's[14] estimation method. I assume quarterly dynamics in the model.

4.1 Externally calibrated parameter

First, I set standard business cycle parameters. The capital share, α, is calibrated to $1/3$, and the discount rate, β, is 0.99. The constant relative risk-aversion parameter, γ, is set to 3, and the quarterly depreciation rate, δ, is calibrate to 0.025 which matches 10% annual depreciation rate.

For the labor market parameters, I am largely indebted to Lin (2014)[1]. The job-seeker share in the generalized matching function, α_h is calibrated to $1/2$, and workers' bargaining share, η, is set to $1/2$[10]. Replacement ratio, $\bar{b}$, is

[10] As Lin (2014)[1] explains, $\alpha_h = 1/2$ is in between 0.4 of Merz (1995)[15] and 0.72 of Shimer (2005)[13]. I follow $\eta = 1/2$ in Lin (2014)[1]

set to 0.75 which is close to Mortensen and Nagypál (2007)[16]. I normalize matching scale parameter, h_0 as one. In the baseline model, I set the wage rigidity parameter, τ to 0.85. Utilizing JOLTS, I calibrate quarterly separation rate ρ_0 to 0.105, as the average monthly separation rate equals 3.5% in the data from January 2001 to May 2017.

I calibrate the autoregressive coefficient of the productivity process, ρ_z, to 0.9058 by estimating the AR(1) process from quarterly output per hour removing the time trend. Lastly, I set the steady state of the standard deviation of productivity shock, $\bar{\sigma}$, to 0.05 following Lin (2014)[1].

Table 2: Externally calibrated parameters

Parameter	Value	Description
α	1/3	Capital share
α_h	1/2	Job-seeker share
β	0.99	Time discount factor
γ	3	Risk aversion
δ	0.025	Quarterly depreciation
η	1/2	Workers' bargaining share
$\bar{b}$	0.75	Replacement ratio
h_0	1	Matching scale parameter
τ	0.85	Wage rigidity
ρ_0	0.105	Quarterly separation rate
ρ_z	0.9058	Productivity autoregressive coefficient
$\bar{\sigma}$	0.05	Steady state standard deviation of productivity shock

4.2 Estimation

The remaining set of parameters except externally calibrated parameters is $\{K_c, K_n, K_v, K_a, \rho_\sigma, \sigma_\sigma\}$. Since the model has the time-varying volatility of the stochastic process, it is not appropriate to use standard Kalman filtering to do the estimation. Therefore, I utilize JP's methodology[14] to draw

the auxiliary latent stochastic volatility. I use the following estimation strategy. First, I draw the time-varying volatility using JP, and I assume that the median value of the drawn stochastic volatility is the true value[11]. Second, assuming the model autoregressive process of time-varying volatility, I estimate the parameters in the volatility process, $\{\rho_\sigma, \sigma_\sigma\}$ using maximum likelihood estimation (MLE). Lastly, given the assumed median value of stochastic volatility, I construct a Kalman filtering system to estimate structural parameter, $\{K_c, K_n, K_v, K_a\}$ using the MLE method.[12]

Before using the JP method, I derive the following first-order state space representation referring to Schmitt-Grohé and Uribe (2004)[19]:

$$Y_t = A(\theta)S_t + B(\theta)e_t, e_t \sim N(0,1)$$
$$S_t = C(\theta)S_{t-1} + D(\theta)u_t, u_t \sim N(0,1),$$

where Y_t denotes observed variables, S_t the state variables, and θ the structural parameters In the model, S_t consists of $\{k_t, n_t, v_t, w_t, z_t\}$.

To utilize the JP method, I use the following prior distribution for $\{K_c, K_n, K_v, K_a, \rho_\sigma, \sigma_\sigma\}$ as in Table 3. First, the mean of K_c is set to 2 which is close to the $S'' = 3$ in JP. From many papers in the labor adjustment cost literature in which the scale parameter distributes mostly between 0 and 1, I set the mean of K_n to 0.5. I assume that the mean of K_v and K_a are slightly lower than of

[11] It is allowed since the credible sets are very tiny for both productivity structural shock and stochastic volatility.

[12] In JP, they also estimate the set of DSGE parameters using the Bayesian method. However, I experience some instability during the estimation of the DSGE parameters since the draws of time-varying volatility continuously change. Therefore, I utilize the JP method only for drawing the time-varying volatility, and then I estimate the structural DSGE parameters using the MLE given the drawn volatility even though there are some information losses.

K_n, so I set the mean of those parameters to 0.45. I set the standard deviations as 20% of the means for all the variables. I set the mean of volatility persistence parameter and the standard deviation of uncertainty shocks using Lin (2014)[1] in which he calibrates those variables close to that number. I iterate 120,000 number in total, and then burn-in half of them. Lastly, I retain one in every five of the iterated results.

Table 3: Prior distribution

Parameter	Distribution	Mean	Standard Deviation
K_c	Gamma	2	0.4
K_n	Gamma	0.5	0.1
K_v	Gamma	0.45	0.1
K_a	Gamma	0.45	0.1
ρ_σ	Beta	0.9	0.05
σ_σ	Inverse gamma	log(1.35)	0.05

To estimate these variables, I use the 8 observable factor: employment, vacancy, real wage, personal consumption expenditure, real output, unemployment, hiring, and recruiting intensity. I use quarterly data from 2001.1Q to 2017.1Q[13]. I use the simple arithmetic average to make quarterly data from monthly data. All the data are detrended using Hodrick-Prescott filter with smoothing parameter $\lambda = 1,600$.

After I draw the structural first-order shock and its stochastic volatility, I regard the median value of the time-varying volatility as the true value. The productivity shock and its stochastic volatility are shown in Figure 7, where shaded area indicates the National Bureau of Economic Research (NBER) Great Recession period.

[13]Sources: employment, unemployment, and hiring from BLS, wage, consumption, and output from FRED, vacancy from JOLTS, and recruiting intensity from DFS.

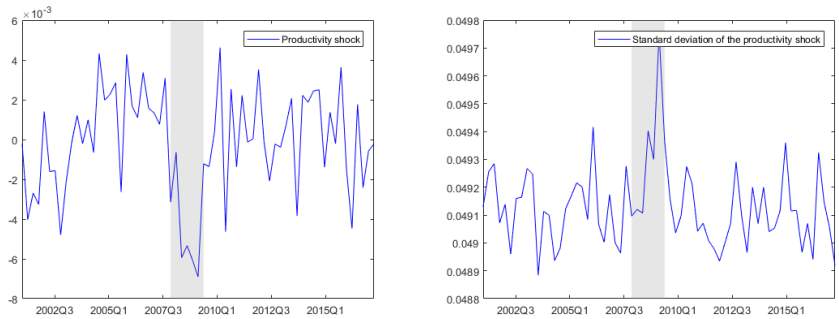

Figure 7: Productivity shocks and the time-varying volatility

Given median stochastic volatility, I use the MLE method to estimate first-order autoregressive process of the stochastic volatility process. Then ρ_σ and σ_σ are estimated as 0.2695 and 0.0491, respectively. In addition, I utilize the MLE method to estimate $\{K_c, K_n, K_v, K_a\}$ using the above first-order state space representation and Kalman filtering. We know that

$$\sqrt{T}(\Theta_{MLE} - \Theta_0) \xrightarrow{D} N(0, \Sigma), \tag{24}$$

where $\Sigma = -T[(\frac{\partial^2 logL}{\partial\Theta\partial\Theta'})|_{\Theta=\Theta_0}]^{-1}$. In this regard, I estimate the remaining parameters, as in Table 4.

Table 4: Estimated parameters

Parameter	Value	Standard Error
K_c	0.2331	3.2979e-09
K_n	0.1642	1.6674e-09
K_v	0.0767	3.0534e-09
K_a	2.7978	1.6733e-09

Note that the median values of estimated structural shocks and their standard deviation are intuitively appealing, however, I need to check the robustness of the model estimation results. Since I combine the JP method and the

MLE method to estimate the structural parameters, a theoretical justification may be needed.

5 Results

5.1 Data and the Model Comparison

Based on the calibrated and estimated parameters, I would like to compare the data and the model-generated data. I draw the model-simulated data by combining first-order state space representation and the structural shocks that I generate during the JP method. Since the structural shocks include the stochastic volatility within it, I do not need to generate further time-varying volatility. Since the model-generated data represent the percentage deviation from the steady state, I do HP filtering after taking logarithm to the data. I estimate the first-order autoregressive process for all the real detrended data and model data, and compare their autoregressive coefficients and the standard errors of the innovations. I use the two wage rigidity parameters, $\tau = 0.85$ and $\tau = 0.95$, to do this work, and Table 5 shows the comparison.

As Table 5 shows, the model-generated vacancy fails to match the moments in the real data, both for the autoregressive coefficient and the standard deviation. As Shimer (2005)[13] argued wage rigidity is helpful to amplify the movement of vacancy and other labor market variables from the productivity shocks. However, although I incorporate ad-hoc wage rigidity in the model, the vacancy exhibits poor data match. In the model without recruiting intensity, the firm controls only vacancy to achieve its hiring goal, so the

Table 5: Data and model-generated moments comparison

	AR(1) coefficient			Standard deviation		
	Data	$\tau = 0.85$	$\tau = 0.95$	Data	$\tau = 0.85$	$\tau = 0.95$
n_t	0.9352	0.9312	0.9367	0.0029	0.0018	0.0023
v_t	0.8599	0.1195	0.2315	0.0503	0.0217	0.0281
w_t	0.8724	0.972	0.9817	0.0024	0.0008	0.0004
c_t	0.8895	0.9301	0.9385	0.0058	0.0004	0.0004
y_t	0.8789	0.9511	0.9516	0.0053	0.0031	0.0032
u_t	0.9255	0.9312	0.9367	0.0401	0.0136	0.0173
h_t	0.8004	0.4191	0.4479	0.0233	0.0159	0.02
a_t	0.8083	0.7107	0.7374	0.0191	0.0236	0.0282

real wage rigidity amplifies the volatility of vacancy. In my interpretation, due to recruiting intensity, a firm controls its recruiting intensity rather than controlling vacancy when it faces real wage rigidity, so the vacancy match can be poor. Note that wage and consumption volatility in the model are not well-matched in the real data.

Figure 8: Data and model-generated comparison: $\tau = 0.85$

5.2 Impulse response from the first- and second order shocks

Given the estimated parameters, I draw the impulse response function by utilizing the third-order perturbation method to observe the impact of the

uncertainty shocks. Therefore the following impulse response function indicates the deviation from the steady states. Note that I use Dynare to generate the impulse response function with third-order perturbation.

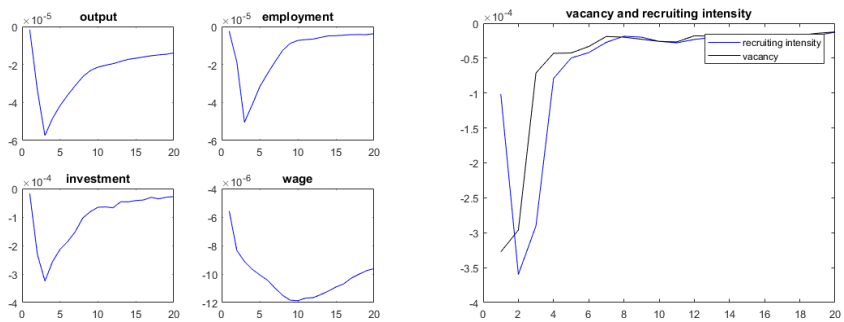

Figure 9: Response from the impact of the uncertainty shocks

Figure 9 shows that responses from the one standard deviation shock on the time-varying volatility process innovation. It is observed that recruiting intensity reacts with a larger magnitude than vacancy from the impact of the uncertainty shocks. Although I need to do further investigation in which the difference in responses is sufficient to explain the dynamics of real data, my model shows the mechanism in which recruiting intensity reacts severely compared to vacancy.

In addition, as previous literature suggests, the impact of uncertainty shocks expands the inaction range, so employment, investment, and output decrease.[14] Therefore, the responses from the uncertainty shocks in my model are consistent with previous findings.

Figure 10 shows the responses from the impact of the productivity shocks. Unfortunately, it fails to match the hypothesis in section 2 in which vacancy

[14]See Dixit and Pindyck (1994)[20] and Bloom (2009)[21]

may react more than recruiting intensity from the first-order productivity shocks. In the figure, the response levels are quite similar for vacancy and recruiting intensity. Therefore, further investigation will be needed to explain this phenomenon. However, the responses for other variables are robust to the previous prediction. When the productivity increases, output, employment, investment, and wage should increase.

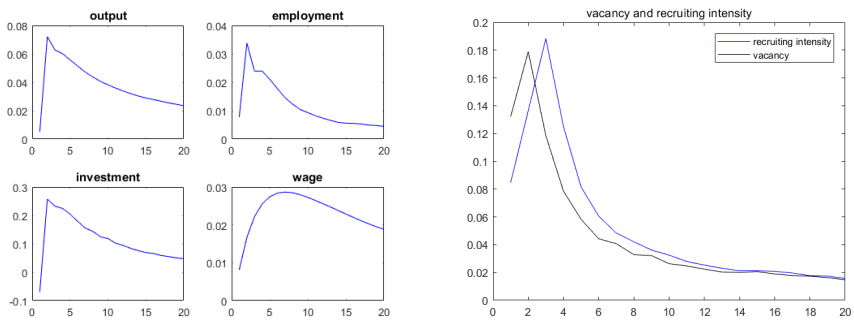

Figure 10: Response from the impact of the productivity shocks

6 Concluding Remarks

In this paper, I attempt to explain the sluggish recovery of recruiting intensity compared to vacancy in the United States after the Great Recession. By observing data and their correlations, I propose the hypothesis that vacancy and recruiting intensity may react differently from the impact of first- and second-order shocks. I adopt a realistic recruiting process in which a firm chooses its vacancies for the next period of hiring, and covers the created vacancies through its recruiting intensity after the demand (productivity) uncertainty is resolved in the next period. That is, there is a difference between vacancy and recruiting intensity in terms of facing the future uncer-

tainty. Since EPU has been quite high since the Great Recession, I expected that the impact of uncertainty shocks would explain the sluggish recovery of recruiting intensity while there has been rapid recovery of first-order variables that quickly recover vacancy.

I utilize a generalized search and matching based DSGE model to materialize my idea. My model successfully reproduced a larger negative response in recruiting intensity from the impact from the uncertainty shocks. However, it failed to generate a greater reaction of vacancy compared to recruiting intensity from the first-order productivity shock. These facts remain the following two prospective works me to do.

First, I need to check the robustness of my parameter estimation. Since I modified JP slightly in a way that utilizes the MLE method by imposing an additional assumption, I need to justify it theoretically. Or, I would try to another estimation method such as SMM to match the data moments. Second, it would be helpful to make a simple toy model that can exhibit my hypothesis in which the different way of facing the uncertainty can create different reactions from the first- and second-order shocks. Although this research remains some works to do support its core idea, I think the model shows another mechanism, or possibility in which vacancy and recruiting intensity may react differently under the real-world recruiting process, due to different ways of reflecting the future uncertainty.

References

[1] Lin, T.-T. T. (2014): “The Role of Uncertainty in Jobless Recoveries."

[2] Hall, R. E., and Schulhofer-Wohl, S. (2013): “Measuring Matching Efficiency with Heterogeneous Jobseekers," mimeo, Stanford University.

[3] Patterson, C., Şahin, A., and Mukoyama, T. (2013): “Job Search Behavior over the Business Cycle," In 2013 Meeting Papers (No. 988), Society for Economic Dynamics.

[4] Hornstein, A., Kudlyak, M. (2016): “Estimating Matching Efficiency with Variable Search Effort," Federal Reserve Bank of San Francisco Working Paper 2016-24.

[5] Davis, S. J., Faberman, R. J., and Haltiwanger, J. C. (2013): “The establishment-level behavior of vacancies and hiring," The Quarterly Journal of Economics, 128(2), 581-622.

[6] Kaas, L., and Kircher, P. (2015): “Efficient firm dynamics in a frictional labor market," The American Economic Review, 105(10), 3030-3060.

[7] Gavazza, A., Mongey, S., and Violante, G. L. (2016): “Aggregate recruiting intensity," (No. w22677) National Bureau of Economic Research.

[8] Baker, S. R., Bloom, N., and Davis, S. J. (2016): “Measuring economic policy uncertainty." The Quarterly Journal of Economics, 131(4), 1593-1636.

[9] Steiger, J. H. (1980): "Tests for comparing elements of a correlation matrix." Psychological bulletin 87(2): 245.

[10] Bachmann, Rudi, K. Cartensen, and M. Schneider: "Firms' Uncertainty and Ambiguity," Work in Progress.

[11] Merz, M., and E., Yashiv (2007): "Labor and the Market Value of the Firm." The American Economic Review, 97(4), 1419-1431.

[12] Gertler, M., L., Sala, and A., Trigari (2008): "An estimated monetary DSGE model with unemployment and staggered nominal wage bargaining." Journal of Money, Credit and Banking, 40(8), 1713-1764.

[13] Shimer, R. (2005): "The cyclical behavior of equilibrium unemployment and vacancies." American economic review, 95(1), 25-49.

[14] Justiniano, A., and G. E., Primiceri (2008): "The time-varying volatility of macroeconomic fluctuations." The American Economic Review, 98(3), 604-641.

[15] Merz, M. (1995): "Search in the labor market and the real business cycle." Journal of monetary Economics, 36(2), 269-300.

[16] Mortensen, D. T., and E., Nagypal (2007): "More on unemployment and vacancy fluctuations." Review of Economic dynamics, 10(3), 327-347.

[17] Yashiv, E. (2016): "Aggregate Hiring and the Value of Jobs Along the Business Cycle."

[18] Kilian, L. (1998): "Small-sample confidence intervals for impulse response functions." Review of economics and statistics, 80(2), 218-230.

[19] Schmitt-Grohé, S., and M., Uribe (2004): “Solving dynamic general equilibrium models using a second-order approximation to the policy function." Journal of economic dynamics and control, 28(4), 755-775.

[20] Dixit, A. K., and R. S., Pindyck (1994): “Investment under uncertainty." Princeton university press.

[21] Bloom, N. (2009): “The impact of uncertainty shocks. econometrica, 77(3), 623-685."

Appendix

A.1. VAR Robustness

A.1.1. 6 Lags

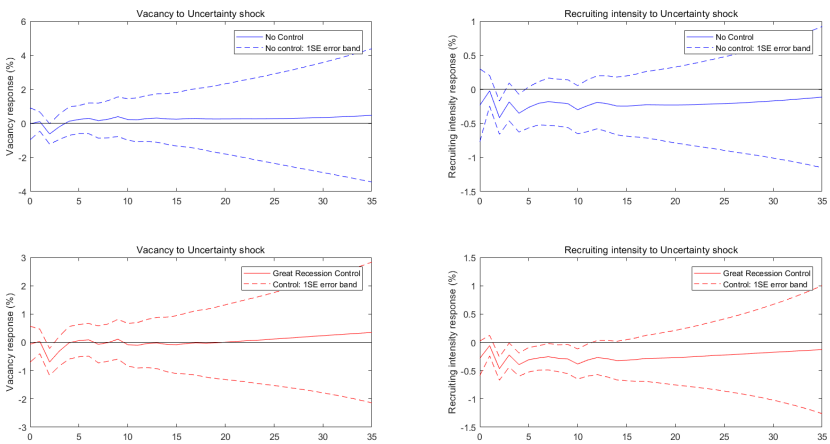

Figure 11: IRFs under the impact of the uncertainty shocks (6 lags)

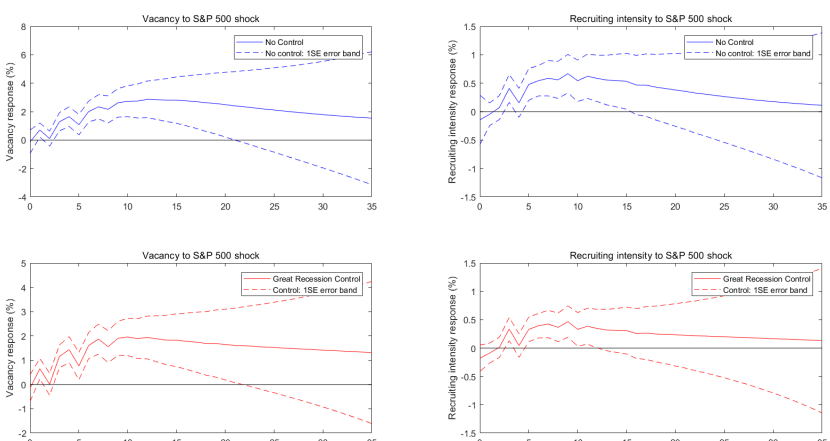

Figure 12: IRFs under the impact of the S&P shocks (6 lags)

국문초록

불확실성 충격으로부터의 채용공고와 채용강도의 상이한 반응과 그 동학에 관한 연구

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이 논문은 2008년 금융위기 이후 미국 내에서 일자리 수에 비해 채용강도의 회복이 더디게 나타났던 경제현상을 살펴본다. 이 현상을 다루기 위해 현실 세계의 채용절차와 불확실성 충격이라는 두 가지 경제적 요소를 도입하여 가설을 세웠다. 채용절차를 계획으로써의 채용공고(vacancy)와 그 계획을 확정 짓기 위해 채용강도 (recruiting intensity)를 정하는 서로 다른 기간에 놓인 두 가지 단계로 구분하여, 채용공고를 상태변수로 설정하였다. 이 방법을 통해 불확실성 충격으로부터의 채용공고와 채용강도의 상이한 반응을 이끌어낼 수 있도록 가설을 세웠다. 실증적으로는 벡터자기회귀모형을 이용하여 불확실성 충격으로부터 채용강도는 통계적으로 유의미하게 반응하는데 채용공고는 그렇지 않은 결과를 이끌어내었다. 또한 가설의 메커니즘을 명확하게 보여주기 위해 일반화 된 탐색-매칭함수를 도입한 동태적확률일반균형모형을 구성하였고, 이 모형을 통해 양의 불확실성 충격에 대해 채용강도가 채용공고에 비해 더 크게 음의 방향으로 반응한다는 것을 보였다.

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주요어: 채용공고, 채용강도, 불확실성 충격, 계획과 실행, 더딘 회복
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