Nonhomogeneous Poisson process for unemployment claims in Washington DC

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ABSTRACT

Unlike majority of the researches which focus on the unemployment rate, this paper studies the number of claims submitted for jobless compensations. Using nonhomogeneous Poisson process, this study constructs Bayesian stochastic analysis models to describe the behaviors of unemployment claims submitted to Washington DC government. Applying the models towards real claim data with implementations of the Markov chain Monte Carlo (MCMC) method, the posterior inferences generated reveals that the model of nonhomogeneous Poisson process with random effects performs better in fitting the data and predicting for future time periods. The purposes of the study are to identify influential socioeconomic factors affecting the claims and to provide precise predictions of the number of claims for the policy makers to improve the allocation of financial resources and carry out effective programs for helping unemployed DC residents in financial hardship to get and retain their jobs, and stabilize local labor force as well as enhance the social stability.

Keywords: unemployment claims, nonhomogeneous Poisson, random effects, MCMC, Bayesian inferences

1. INTRODUCTION

Controlling unemployment at a reasonable low level is one of the main targets of economic policies for regional and national governments. Large size of unemployed labor force not only means the waste of economic resources, but also casts financial and psychological hardship on families of those unemployed labors. In addition, as Raphael and Winter-Ebmer (2001) and Aaltonen et al. (2013) pointed out, higher unemployment could bring instabilities such as property crimes to the society.

To study the unemployment problem, many researchers focused on analyzing the behaviors of individual labors and firms under different labor market conditions. Classical labor theory describes unemployment as the disequilibrium of the supply and demand of labors given a wage rate deviating from its equilibrium position in a competitive market (Phillips, 1958; Mankiw, 2009), although it is difficult to reach a steady state of the labor market with natural and voluntary unemployment (Tobin, 1972). And the search theory of unemployment studies the optimizing behavior of labors and firms in response to different market conditions including new labor market policies such as minimum hourly wage rate and unemployment compensations (Diamond, 1982; Fitzgerald, 1998).

For the policy makers, the aggregate level unemployed population and the unemployment rate are more of their interest, compared to individual level job separation and hiring, as the former closely relates to the unemployment policies and public finance of government agencies. Therefore, numerous researches have been conducted to predict unemployment rate and analyze its relationship with other socioeconomic factors. Albeit, few studies targeted at the claims for unemployment compensations which were submitted to the local governments by those who recently lost their jobs.

The claims of unemployment compensations directly influence government's fiscal expenditures to reduce the hardship of the unemployed persons and stabilize the local workforce and the economy. It can be treated as the indicator for the unemployment during the coming months and quarters. This paper focuses on analyzing the behaviors of new unemployment claims the government of Washington D.C. has been handling. It is noted that a large proportion of people working in D.C. are residents of neighboring states. According to DeWitt (2019), in December 2018 there were around 799,100 people working in D.C., and among all D.C. residents about 384,700 were employed which included those hired by employers both inside and outside the district. Therefore, it is reasonable to conclude that a significant proportion of those who submit claims to D.C. Department of Employment Services (DCDES) for unemployment compensation are residents of other states especially of Virginia and Maryland. And it is beneficial for the D.C. government to obtain precise estimates of the unemployment claims for a better allocation of financial resources and providing effective programs such as vocational skill training programs to help the unemployed D.C. residents to get and retain their jobs.

The rest of the paper starts with Section 2 which provides a brief review of the researches conducted in regard to the unemployment claims as well as relevant statistical analysis models. Section 3 establishes modulated and random effects nonhomogeneous Poisson processes for the unemployment claims. Empirical analysis is carried out in Section 4, using time series data of new unemployment claims submitted to the DCDES. Section 5 concludes this study and provides recommendations for future research.

2. REVIEW OF RESEARCHES OF UNEMPLOYMENT CLAIMS

Unemployment is a key factor influencing people's lives and economic development of a society. While a waged person losses her/his job due to the decision of employment termination by the employer, she/he can claim for unemployment compensation and is reported as being unemployed. Due to its negative impact on personal lives and the economy, abundant researches have been conducted to analyze the unemployment with the purposes to understand its causes and other characteristics. Besides many economists who applied classical labor theory and search theory to analyze the unemployment phenomenon, some researchers focused on predicting and analyzing the influential factors for the spell of the unemployment. For example, Meyer (1990) studies the impact of the unemployment insurance on unemployment spell. Dockery (2004) used job search method to analyze the experience of unemployed Australians in terms of perceived barriers to the employment. And Rothstein (2016) focused on factors relating to unemployment spell.

Some other studies targeted at the relationship between the unemployment rate and other socioeconomic factors. For example, Papke (1994) identified significant impact of the enterprise zone program for reducing the unemployment. Rees and Mocan (1997) suggested a negative relationship between the unemployment rate and the high school dropout ratios. Askitas and Zimmermann (2009) found strong correlation between the Internet keyword searches and the unemployment rates. Wooldrige (2013) presented an autoregressive (AR) model for the relationship between crime and unemployment rate, which includes inflation with a lag as a covariate.

Few researches studied unemployment claims directly. Most extant researches used unemployment claims as an indicator for analyzing other economic factors. Gavin and Kliesen (2002) included unemployment claims as one of the labor market variables in the AR processes for predicting real GDP growth and unemployment rate. D'Amuri and Marcucci (2010, 2017) implemented AR and ARMA (autoregressive and moving average) models and used both Google index and unemployment claims as indicators for predicting the unemployment rate. To our best knowledge, the only published study which focus on the unemployment claims was conducted by Choi and Varian (2009), in which the authors developed an AR(1) model for the logarithm of the initial unemployment claims and claimed that the Google trends data can improve the prediction of initial claims.

In this paper, the nonhomogeneous Poisson process (NHPP) is applied to describe the behaviors of the quarterly unemployment claims submitted to the D.C. government. The Poisson process models have been extensively applied to study the number of occurrences of specific events. For example, Sinha (1993) used modulated Poisson process in survival analysis, Lynn (2004) proposed a NHPP model for describing bond issuers' default behavior, Soyer and Tarimcilar (2008) established a MPPM model for the call center arrivals, Merrick et al. (2005) used modulated Poisson process for the reliability analysis, and Aktekin et al. (2013) applied a dynamic Poisson process to study the occurrences of the mortgage defaults. Next two section will elaborates that for the number of unemployment claims, a NHPP model can appropriately describe its behavior and can be used to predict the expected claim numbers for future time periods.

3. NONHOMOGENEOUS POISSON PROCESSES FOR THE UNEMPLOYMENT CLAIMS

Let $N(t)$ be the number of unemployment claims in a time interval denoted as t, which follows a nonhomogeneous Poisson process (NHPP) with cumulative intensity function $\Lambda(t)$, the distribution of $N(t)$ can be described using the formula

$$P(N(t)=n)=\frac{(\Lambda(t))^n}{n!}\exp[-\Lambda(t)] \quad (1)$$

And the intensity function of the unemployment claim rate, $\lambda(t)=\frac{d}{dt}\Lambda(t)$, while including the effects of external covariates, can be stated as,

$$\lambda(t,X(t))=\lambda_0(t)\exp[\theta' X(t)] \quad (2)$$

where $\lambda_0(t)$ is the baseline intensity function which can be assumed to be exchangeable over different time intervals with the same length (Marrick *et al*, 2005). $X(t)$ is a vector of covariates, and $\boldsymbol{\theta}$ is a $p\times 1$ vector of parameters. Further, a power law model can be specified for the cumulative baseline intensity function, denoted as

$$\Lambda_0(t)=\alpha t^{\gamma} \quad (3)$$

where α and γ follow independent Gamma prior distributions with known parameters (a_α, b_α) and (a_γ, b_γ). The covariate vector θ is assigned a multivariate Normal prior distribution

$$\theta \sim MVN(\mu, W) \quad (4)$$

in which the mean vector μ and covariance matrix W are known values.

Given unemployment claims data $D=\{n_1,n_2,\cdots,n_T\}$, where n_i denotes number of unemployment claims during the ith time period, the likelihood function of the model becomes

$$L(\alpha,\gamma,\theta;D)=\prod_{i=1}^{T}\frac{\{\alpha(t_i^{\gamma}-t_{i-1}^{\gamma})\exp[\theta' X(t)]\}^{n_i}}{n_i!}\exp\{-\alpha(t_i^{\gamma}-t_{i-1}^{\gamma})\exp[\theta' X(t)]\} \quad (5)$$

and the joint posterior distribution of the model, which can be labeled as modulated Poisson process model (MPP) according to Marrick *et al*. (2005), is stated to be proportional to,

$$p(\alpha,\gamma,\theta|D)\propto L(\alpha,\gamma,\theta;D)\alpha^{a_\alpha-1}\gamma^{a_\gamma-1}\exp\left\{-\left[b_\alpha\alpha+b_\gamma\gamma+\frac{1}{2}(\theta-\mu)' W^{-1}(\theta-\mu)\right]\right\} \quad (6)$$

The joint posterior distribution cannot be obtained analytically, in which case the posterior and predictive analyses of the model will be carried out using Markov chain Monte Carlo (MCMC) methods. And the MCMC methods (Gilks *et al*., 1996) are implemented using the WinBUGS software developed by Spiegelhalter et al. (1996) and Lunn et al. (2000).

With posterior samples generated by the MCMC algorithms, different posterior inferences can be obtained using Monte Carlo estimates. Given [(α^1, γ^1, θ^1), …, (α^G, γ^G, θ^G)], a posterior sample of size G, posterior distributions of parameters can be obtained using density estimates from the marginal samples. And the mean estimate of the number of unemployment claims during a specific period can be obtained using Monte Carlo approximation

$$E(n_t|D)\approx\frac{1}{G}\sum_{g=1}^{G}\left[\alpha^g\left(t_i^{\gamma^g}-t_{i-1}^{\gamma^g}\right)\exp\left[\theta^{g\prime} X(t)\right]\right] \quad (7)$$

Very likely, sometime the covariates included in the MPP model cannot reflect the complicated socioeconomic environment. For the consideration of possible sources of unknown variation, a random effects term corresponding to each time period can be included in the intensity function denoted as,

$$\lambda(t,X(t))=\lambda_0(t)\exp[\theta' X(t)+\varepsilon_t] \quad (8)$$

where ε_t is the time specific random effects term. It can be further assumed that ε_t's are conditionally independent, following a normal prior distribution

$$\varepsilon_t|\tau \sim N(0, \tau_\varepsilon^{-1}) \tag{9}$$

where the unknown precision can be described by a gamma prior distribution, $\tau_\varepsilon \sim Gamma(a_\tau, b_\tau)$, with specified hyperparameters a_τ and b_τ. Alternatively, the baseline intensity parameter α can be replaced with exchangeable sequence of parameters α_t's, which creates a mixed effects structure. In this study, the focus is on the form of only the random effects term. Therefore, the likelihood function of the Poisson process with random effects (REPP) model can be stated as

$$L(\alpha, \gamma, \theta, \varepsilon_t{}'s; D) = \prod_{i=1}^{T} \frac{\left\{\alpha\left(t_i^\gamma - t_{i-1}^\gamma\right)\exp\left[\theta' X(t) + \varepsilon_i\right]\right\}^{n_i}}{n_i!} \times \exp\left\{-\alpha\left(t_i^\gamma - t_{i-1}^\gamma\right)\exp[\theta' X(t) + \varepsilon_i]\right\} \tag{10}$$

and the joint posterior distribution of the model is proportional to,

$$p(\alpha, \gamma, \theta, \varepsilon_t{}'s, \tau|D) \propto \prod_{i=1}^{T} \tau^{\frac{1}{2}} \exp\left(-\frac{\tau}{2}\varepsilon_i^2\right) \frac{\left\{\alpha\left(t_i^\gamma - t_{i-1}^\gamma\right)\exp[\theta' X(t) + \varepsilon_i]\right\}^{n_i}}{n_i!} \times \exp\left\{-\alpha\left(t_i^\gamma - t_{i-1}^\gamma\right)\exp[\theta' X(t) + \varepsilon_i]\right\} \alpha^{a_\alpha - 1}\gamma^{a_\gamma - 1}\tau^{a_\tau} \times \exp\left\{-\left[b_\alpha \alpha + b_\gamma \gamma + b_\tau \tau + \frac{1}{2}(\theta - \mu)' W^{-1}(\theta - \mu)\right]\right\} \tag{11}$$

Same as that for the MPP model, the joint posterior distribution cannot be obtained in the closed form, and the MCMC methods will be applied to generate posterior samples for inference purposes.

4. EMPIRICAL ANALYSIS OF DC UNEMPLOYMENT CLAIMS

For the unemployment claims data, we select monthly data of initial unemployment claims from the Bureau of Labor Statistics (BLS) of the Department of Labor, which covers the period from January 2005 to March 2019. For influential covariates, three variables are included in the analysis. The first covariate is the size of labor force in Washington DC. As discussed in Sincavage (2004) and Hornstein & Kudlyak (2019), it is reasonable to argue that during the period of economic downturn, the area with larger labor force has higher unemployment pressure. The second covariate is the unemployment population in Washington DC metropolitan area. Increase of the unemployment population may cause more people in financial difficulties to claim for unemployment compensation. Records of the above two covariates can be obtained from the database of the BLS and D.C. Economic Indicators reports provided by the Office of the Chief Financial Officer of Washington, DC. As unemployment claims are closely related to GDP (Gavin & Kliesne, 2002, and Feng et al., 2017), in the following analysis the GDP of the Washington DC is chosen to be the third covariate in the MPP and REPP models.

In the data set, GDP data is reported by the Bureau of Economic Analysis (BEA) quarterly while other series are provided on a monthly basis. We transform each monthly-level data into quarterly series. More specifically, we aggregate initial claims, and calculate average labor force and average unemployment population numbers in the same quarter.

Based on the time-series plot in Figure 1 (Appendix) of initial unemployment claims submitted to the DCDES, it is clear that the numbers of people claimed for the compensation increased significantly during the financial crisis period of years 2008 and 2009, after that it gradually came down (except in the second half of the year 2013) to the year 2005 level around

4,000 claims. But interestingly the claim number climbed up again to a much higher level during the first quarter of 2019.

Applying the MPP model to the unemployment claim data, proper but diffused priors were used for all parameters in the model. The MCMC algorithm was run with a burn-in sample of 10,000 iterations and 10,000 posterior samples were collected for inferential analysis. Based on the analysis using the BOA program of Smith (2007), all parameters have their posterior samples converging to the stationary distributions. To save the space, Figure 2 (Appendix) provides the histograms and trace plots of posterior samples of three parameters within the MPP model, which demonstrate the convergency of posterior samples. The posterior summaries of the parameters are presented in Table 1 (Appendix).

The posterior statistics point out that the DC labor force and metropolitan area unemployment populations have positive impact on the initial claims, which are consistent with the arguments that larger populations of labor force and the unemployed in the area could result in higher claims submitted for unemployment compensations. And when the GDP of Washington DC is increasing, the economic growth could create more job positions, thereby decreasing the unemployment claims.

While applying the MPP model to estimate the unemployment claims, shown in Figure 3 (Appendix), it is obvious that the model does not provide a good fit for the real observed claim records, which suggests that some important influential covariates are missing from the model.

To take care of the unknown influential sources, the REPP model is applied to the analysis of the claim data. Table 2 (Appendix) presents the posterior summaries of main parameters of the REPP model. Same as those in the MPP model, the labor force and unemployment at metropolitan area have positive impact on the initial unemployment claims, while the GDP of Washington DC negatively influences the claim number. The validity of using the posterior summaries for inference purposes is guaranteed by the convergencies of the posterior samples generated from the model. Figure 4 (Appendix) presents the histograms and trace plots of posterior samples of three parameters, and those of the rest parameters are showing similar converging patterns, which are not presented here.

The estimates of the quarterly unemployment claims, obtained using the REPP model, are plotted in Figure 5 (Appendix). Compared to the MPP model, there is significant improvement from the REPP model in fitting the real unemployment claim records. Albeit, to conclude whether the later is really performing better than the MPP model, it is necessary to compare both models' performances in predicting unemployment claims for the future periods. In doing so, an out-of-sample cross validation analysis is carried out for the comparison purpose.

In cross validation analysis, the first 52 quarters' data are used as the training set for estimating both MPP and REPP models. Then both estimated models are applied to obtain the forecasts for the next five quarters. Both models are compared using both mean squared errors (MSE's) and mean absolute percentage errors (MAPE's) of the forecasts projected. Table 3 (Appendix) lists the comparison results, which demonstrate that the REPP model performs better than the MPP model.

5. CONCLUSIONS AND SUGGESTIONS

This paper studied the numbers of unemployment claims submitted to the Department of Employment Services of Washington DC. Two models, the modulated Poisson process model and random effects Poisson process model, were constructed to describe the nonhomogeneous behavior of the unemployment claims and capture influences from external factors. Applying the models towards quarterly unemployment claim data, it was found that the number of claims were positively influenced by the sizes of DC labor force and unemployment population around the metropolitan area. Besides, both models concluded in the negative connection between the unemployment claims and the GDP levels of Washington DC.

Comparing the performances of the models, it was noted that the REPP model not only fit the data better, but also provided more precise out-of-sample predictions than the MPP model. Therefore, it is more appropriate to be applied for estimating future number of unemployment claims, to help DC government allocate financial resources better for reducing the hardship of the unemployed persons and providing effective training programs to stabilize the local workforce and the economy.

To further this research, more potential influential covariates can be included into the models, to identify important socioeconomic factors impacting the unemployment claims. Besides, with the availability of data for each person who submitted the claim, additional models can be established at individual level to describe personal decisions on the claim and influential characteristics such as industrial sector the person worked in, income level, marital status and family size, educational background, etc. With individual level models, aggregately the estimate of the overall number of claims can be obtained, meanwhile, the government agencies can establish more effective policies targeting on individuals with certain demographic and socioeconomic traits.

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APPENDIX: TABLES AND FIGURES

Table 1: Posterior summaries of the MPP model parameters

Parameter	Mean	Standard Error
α	2410.500	4.861
γ	1.532	0.001
$\theta_{\text{Labor-force}}$	6.604	0.021
$\theta_{\text{Metro-Unemployment}}$	1.298	0.019
θ_{GDP}	-9.693	0.006

Table 2: Posterior summaries of the REPP model parameters

Parameter	Mean	Standard Error
α	4.474	0.066
γ	1.034	0.001
τ	123.959	0.852
$\theta_{\text{Labor-force}}$	3.002	0.020
$\theta_{\text{Metro-Unemployment}}$	0.670	0.024
θ_{GDP}	-0.918	0.050

Table 3: Cross validation comparison of MPP and REPP models

	MPP model	REPP model
MSE	10.953	1.059
MAPE	40.796%	16.927%

Figure 1: Time-series plot of new unemployment claims in Washington, DC

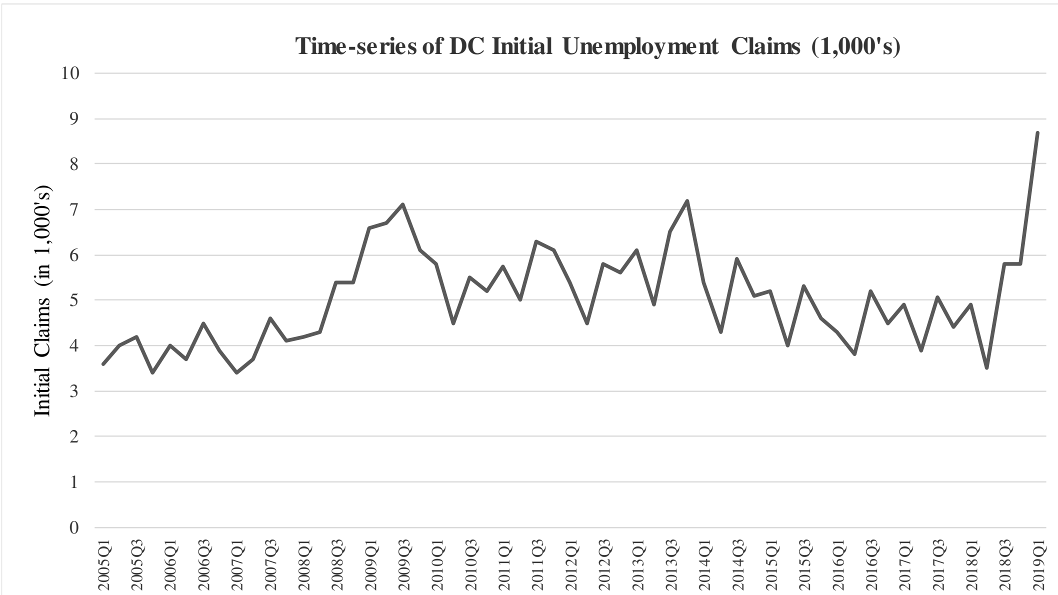


Figure 2: Histograms and trace plots of posterior samples of selected MPP parameters

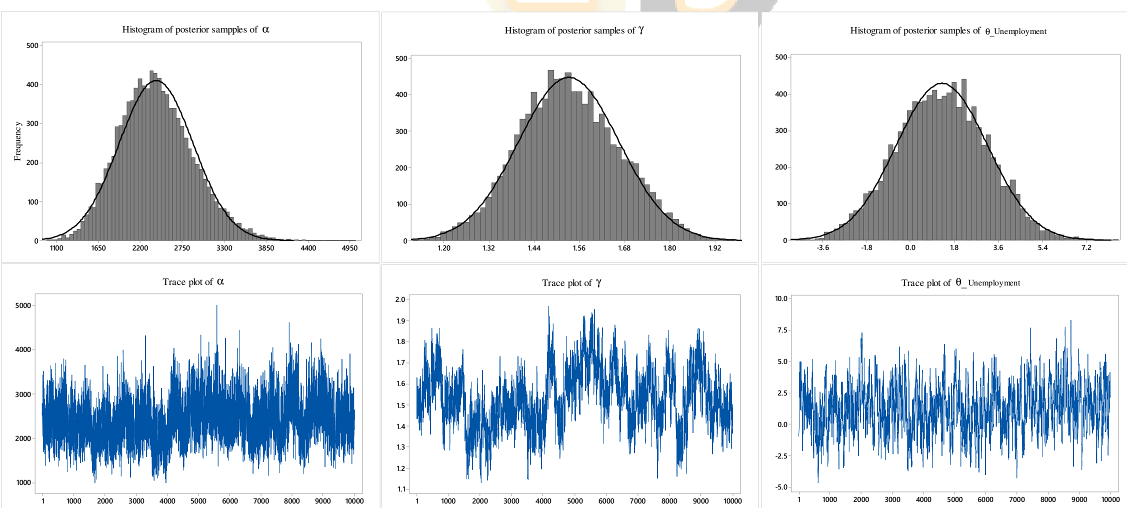


Figure 3: Overlay plot of unemployment claims and MPP model predictions

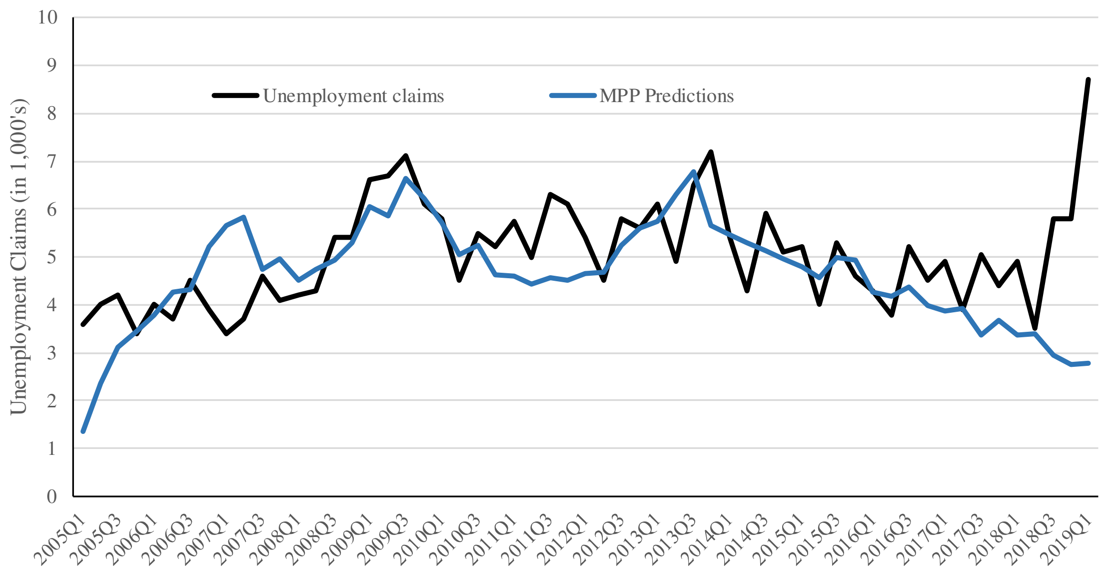


Figure 4: Histograms and trace plots of posterior samples of selected REPP parameters

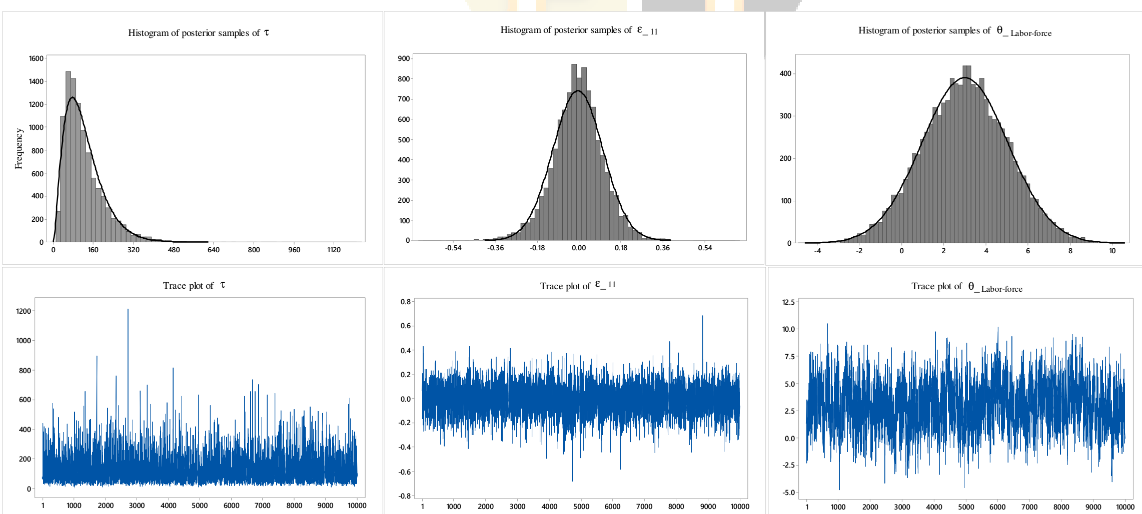
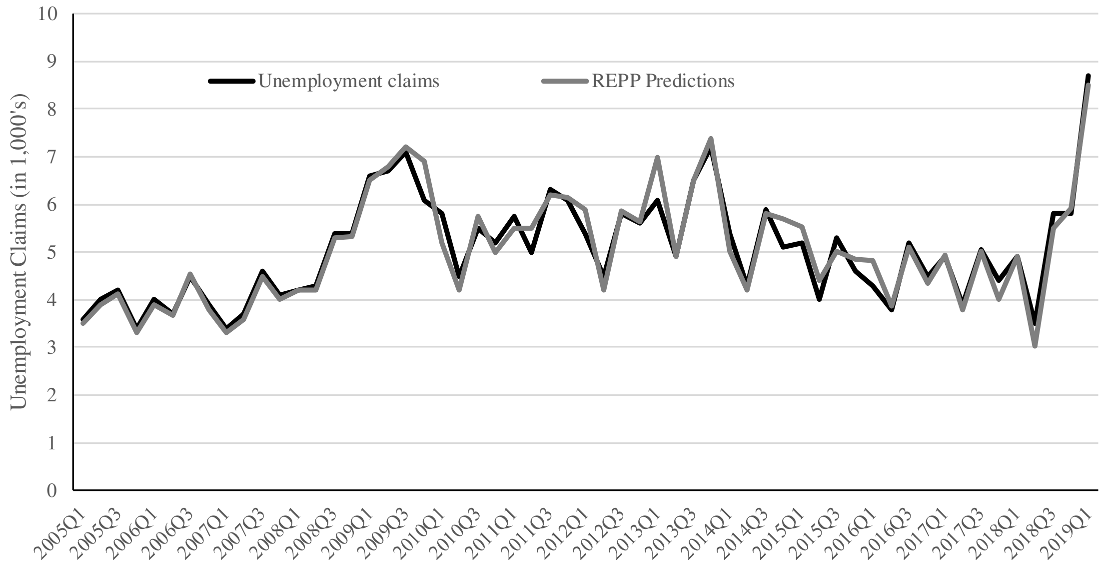


Figure 5: Overlay plot of unemployment claims and REPP model predictions


Unemployment claims
REPP Predictions
Unemployment Claims (in 1,000's)
10
9
8
7
6
5
4
3
2
1
0
2005Q1
2005Q3
2006Q1
2006Q3
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