Measuring the Effectiveness of the Austrian Anti-Eviction Response during the Start of the COVID-19 Pandemic

Selim Banabak[*], Tatjana Neuhuber[†], Antonia Schneider[‡]

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Abstract

During the first wave of COVID-19, numerous OECD member states introduced short-term tenant protection policies, including Austria. The COVID-19-Justiz-Begleitgesetz enacted in early 2020 allowed for deferral of housing rents due between the beginning of April and the end of July up to the end of December. Furthermore, the short-term extension of contracts expiring in that period, as well as a moratorium on evictions for up to six months, were also possible. This paper investigates whether the measures taken succeeded in retaining eviction rates at pre-crisis levels and whether there is significant variation across Austrian states. Although we saw a clear drop off in the absolute number of evictions from 4208 to 3094, there has already been an ongoing downward trend in eviction cases since 2006, which needs to be considered. Thus, both long-term trends in evictions, as well as underlying economic drivers, need to be considered to evaluate the set of anti-eviction policies taken at the federal level. To formally test the hypothesis of reduced eviction cases in 2020, we estimate a Poisson-Panel Model using panel data on evictions and a set of socioeconomic indicators observed between 2010 and 2020 across 85 Austrian districts. We employ Bayesian advanced auxiliary mixture sampling to estimate the econometric model. We find that eviction rates were reduced significantly during 2020 across states, also after accounting for long-term regional trends and pandemic-induced economic downturn.

Keywords: Evictions, COVID19, Austria, Bayesian Poisson Panel Regression, Auxiliary Mixture Sampling, SSVS

[*]Research Unit Urban and Regional Studies, TU Wien
[†]Department of Public Finance and Infrastructure Policy, TU Wien
[‡]Department of Public Finance and Infrastructure Policy, TU Wien

1 Introduction

During the first wave of COVID-19, numerous OECD member states introduced short-term tenant protection policies (OECD, 2020) as a reaction to declining incomes caused by rising unemployment and the wide spread of short-time work schemes. Those policies typically included placing moratoriums on evictions, holds on shutting off utilities due to nonpayment, prohibiting late rent fees, as well as financial support measures such as rent supplements. Especially in a time where staying at home was considered an obligation, having a home is essential. In the case of Austria, which has a rental share of 42,7 % (Statistik Austria, 2020), protecting tenants was regarded as a priority.

The *COVID-19-Justiz-Begleitgesetz*[1] enacted in early 2020, allowed for deferral of housing rents due between the beginning of April 2020 and the end of July 2020 up to the end of December. However, late payment interest may still be claimed by the landlord. Furthermore, contracts expiring in that period were allowed to receive a short-term extension, again until the end of December. Lastly, it included a moratorium on evictions for up to six months. The policy was lifted by the end of December 2020. Although we saw a clear drop off in the number of evictions from 4,208 in 2019 to 3,094 in 2020, there has also been a strong downward trend in the number of evictions since 2006.

We are thus interested in whether the measures taken succeeded in preventing a substantial increase of evictions across Austria and if this effect varies across Austria. Generally, Austria has below EU average eviction cases, with 0.06% of the population facing an eviction every year. However, cases are unevenly distributed across the country, especially varying with the degree of urbanisation - the respective rate in Vienna standing at 0.17% (European Commission, 2016). On the other hand, the most common cause of evictions is arrears in rent payments which are directly linked to both disposable income of households and indebtedness. According to eviction

[1]see §6 Abs 1 2. COVID-19-JuBG BGBl. I 24/2020

prevention services, about 80% of their clients are threatened by eviction due to rent arrears, while only 20% of evictions are connected to anti-social behaviour, noise or littering (Schoibl, 2013). Again, in Vienna, 95% of tenants affected by evictions were just unable to conduct rent payments (Volkshilfe Wien, 2011). Thus, we need to consider both long-term trends in evictions as well as underlying economic drivers. Using panel data on evictions observed across 85 Austrian districts, we estimate a Bayesian Poisson-Panel Model with Stochastic Search Variable Selection to formally test the hypothesis of a significant reduction in evictions across Austria in 2020 and a respective increase in 2021.

2 A brief survey of the literature

Austria is only one of many countries that implemented an eviction ban at the beginning of the COVID-19 pandemic. Many other countries, like Argentina, the United States, the United Kingdom, Italy and Germany, have enacted housing policies to prevent a surge of evictions during the crises. Measures included but are not limited to rent freeze, eviction bans, mortgage relief and rent subsidies (Kholodilin 2020). While countries implemented policies tied to different narratives, they shared one common goal: the reduction of evictions during the crisis. There is evidence, that such policies have indeed succeeded in decreasing the number of evictions (see, e.g. Greenberg et al. 2021, Cowin et al. 2020, Martyn et al. 2021). Moreover, some policies, such as the combination of hearing and filing bans, seem to be especially efficient in bringing down eviction rates (Cowin et al. 2020). Yet, as the pandemic continued, policies were lifted and as a consequence, eviction rates not only increased again but even succeeded the pre-crisis level in some cases (Finger et al. 2021).

Vocal critique has been voiced about how many governments handled this situation. It is argued that policies were lifted too soon (Fontenot 2021) or not thought-through enough (Zhao 2020). Accordingly, Alexander (2021) emphasizes a "housing-first" strategy which fosters housing affordability and impedes the filing of evictions. Similarly, Vilenica et al. (2020) call for long-term solutions that are characterized by in-depth reforms instead of austerity and individualistic measures. More generally, it is highlighted that COVID-19 exaggerated the need for extended housing policies reform and the decommodification of the housing market (Blakeley 2021)

While economic shocks or other crises, such as the COVID-19 pandemic, are a major cause of rising evictions, there are several others that have been identified in the literature. For instance, Chum (2015) found a positive effect of gentrification on evictions, especially in areas where the ratio of people with tertiary education increases but average income remains more or less stable. Another study by Vives-Miró et al. (2015) concludes that low-status areas in Majorca experience higher eviction rates than medium or high-status areas. Additionally, Otter et al. (2017) note that people who are unemployed or receive social assistance are more likely to be evicted. These findings generally indicate that areas with a higher share of people with a university degree and higher income demonstrate lower eviction rates. Hence, economic and social vulnerability might increase the chance of being evicted.

Clark (2016) further argued that disruptive family events, such as job loss or divorce, can cause housing issues. Other factors that might increase the likelihood of eviction are having a migrant background or being a single mother (Laniyonu 2019). Further, the regulatory welfare state and social regulation are found to be important indicators for eviction rates (Haber 2015). Accordingly, capitalist practices and an increasing reliance on home ownership might force low-income renters out of their homes. In contrast, other institutional arrangements and settings, such as rent affordability policies, social housing and living wage ordinances, are considered vital to prevent evictions (Hartman and Robinson 2003). While most studies looking at the effect of COVID-19-related housing policies do so using only descriptive statistics, there is still a missing link between the effects of COVID-19 eviction ban policies and other causes of evictions. This study aims to fill this gap by incorporating several explanatory variables into the model specification while also explicitly testing for the effects of COVID-19.

3 Data and Descriptives

To estimate our model, we use a unique panel dataset of annual observations across 85 spatial units mainly corresponding to Austrian court districts, which are themselves nested in the Austrian provinces. Yearly observations span from 2004 to 2021 and include the total number of eviction cases as well as a number of potential explanatory variables. First of all, population size is an obvious choice when modeling the mean of eviction counts. Total labor income serves as an available proxy for the general economic performance of a district, while the number of people who are unemployed and low earners[2] provide more detailed information on the size of the economically vulnerable population. Mean housing rents provide information regarding the other side of housing affordability.

We also consider the number of divorces as they are together with job loss, declining income and housing affordability one of the five most cited reasons of excess indebtedness (Schuldnerberatung, 2020). Further, the dependency ratio (people older than 65 and younger than 15 divided by the overall population) and the education ratio (people with mandatory education divided by people with tertiary education) are considered. To test for changes in eviction rates across Austrian's provinces, an interaction term COVID-19*Province is also included(where a yearly dummy for 2020 and a dummy for each province is created)[3]. Table 1 provides an overview of all variables and their sources.

[2] defined by yearly labor-income below 12,000 Euros.

[3] We included provinces rather than districts as legislation is made on a provincial level rather than district level.

Table 1: Variables and Sources

Variable	scale	timelag	source
Evictions Count	count	-	Statistics Austria
Province*Covid-19 Year	binary	-	-
Mean district-level Income	log	✓	Statistics Austria
Population	log	✓	Statistics Austria
Unemployment Count	log	✓	Statistics Austria
Low Wage Households	log	✓	Statistics Austria
Rent/m2	log	✓	Austrian Economic Chamber
Number of rental flats	log	-	Statistics Austria
Divorce Count	log	✓	Statistics Austria
Education Ratio	log	-	Statistics Austria
Dependency Ratio	log	-	Statistics Austria

Note: All variables measured on court district level (85 units) between 2009 and 2020

Evictions were observed on the level of the original 115 Austrian court districts, while the remaining variables are sourced on the level of the 94 political districts. Spatial units are then constructed to achieve a proper nesting structure, leaving us with a total of 85 units. Figure 1 depicts the relative development of selected variables aggregated on the province level as well as evictions on the district level. 2009 was chosen as the base, and the dashed lines indicate each district within the given province. Some lines appear interrupted as the change in the number of evictions exceeds the chosen limits of the graph. However, if a higher limit is chosen, the development of other variables becomes unclear.

It becomes apparent that all provinces but *Burgenland* exhibit a downward trend in the number of eviction cases which varies considerably in strength. Also, the dropoff in evictions during the first year of the pandemic is visible while unemployment is spiking across provinces. In general, income and rent also increased in most provinces while most other variables experienced a slight decrease or remained more or less stable over time.

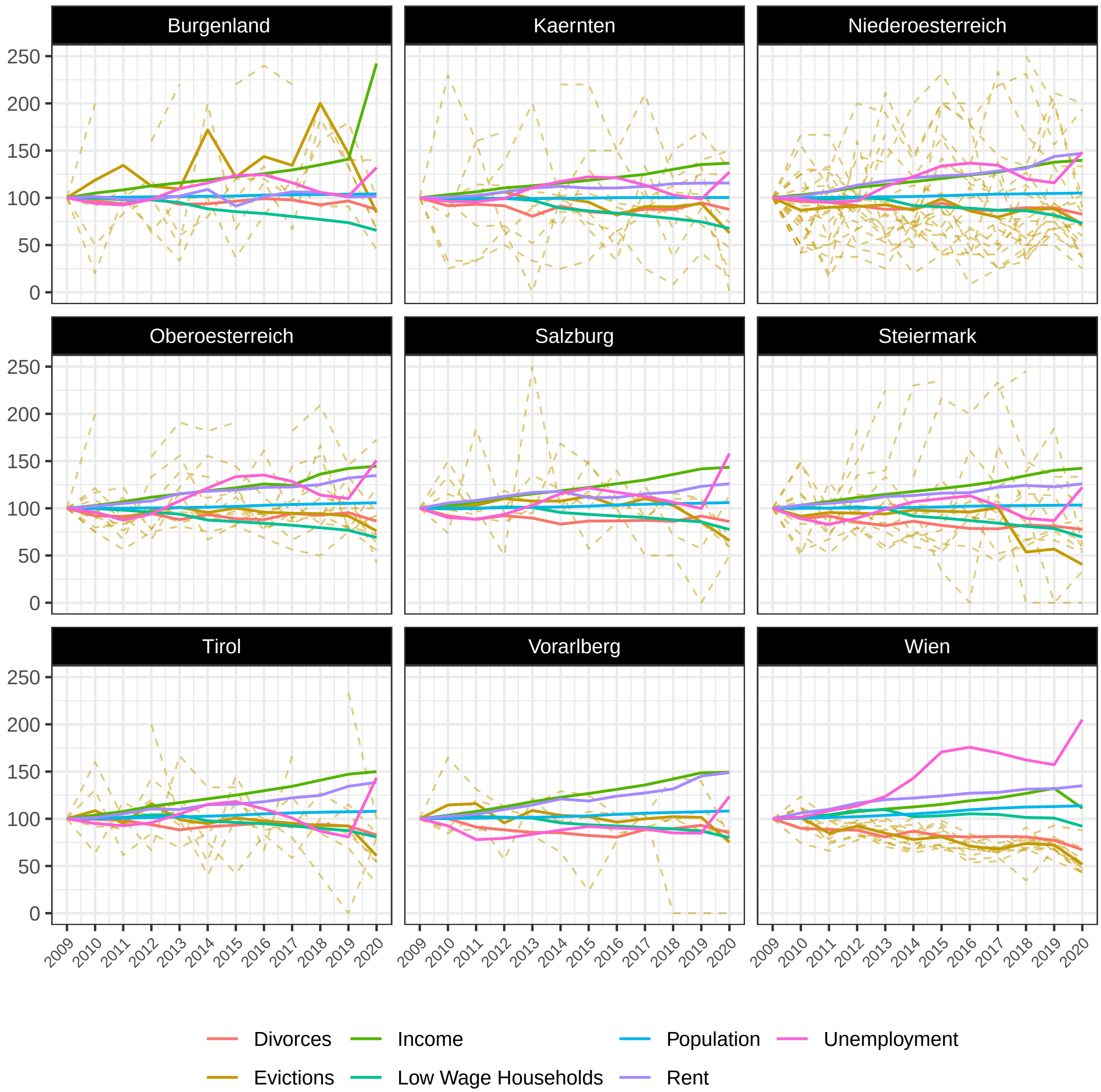

Figure 1: Development of selected variables. 2009=100

4 Methodology

In order to analyze whether the anti-eviction policy was successful in preventing the surge of eviction rates, a Bayesian Poisson-Panel Model with offset and Stochastic Search Variable Selection is employed. The next chapter presents the general model before discussing the estimation method and variable selection process.

4.1 Model

Let $y = \{y_{it}\}$ be count data for $i = 1, ..., n$ regions and $t = 1, ..., T$ time periods. A common model for count data is the Poisson model.

$$y_{it}|\beta, \alpha_i \sim Po(\mu_{it}) = Po(pop_{it}\lambda) \tag{1}$$

where $\mu_{it} > 0$ is the mean of the distribution, which is the product of the exposure *pop* and the intensity parameter λ:

$$\mu_{it} = e_{it}\lambda = E(y_{it}|\beta, \alpha_i) = pop \times exp(X_{it}'\beta + \alpha_i). \tag{2}$$

with β denoting the parameter vector where $\beta = (\beta_0, \beta_1, ..., \beta_k)'$, X_{it} is the covariates vector of length k for β and α_i denotes a random intercept for each unit.

The dependent variable is count data of eviction cases per spatial unit i. The population at time t in unit i acts as an offset. We use random effects and state-specific time trends to model the number of evictions expected per spatial unit. In order to test whether policies indeed succeeded in the prevention of exceptionally high eviction numbers due to the COVID-19 crisis, we further introduce state-specific dummies for the pandemic year 2020. All explanatory variables were presented in Table 1.

4.2 Estimation

In order to estimate the model parameter β, MCMC methods are employed. However, due to the non-linearity of the Poisson model, standard Gibbs sampling is not feasible, as discussed in Geman and Geman (1984). Therefore, the Metropolis-Hastings (MH) algorithm is frequently employed when working with Poisson regression models (e.g. Chib et al. 1998, Diggle et al. 1998, Ma and Kockelman 2006, Stamey et al. 2008). MH algorithms are convenient when dealing with nonlinear models since they can deal with unrecognizable conditional distributions. It separates the distribution into two parts, one that is recognizable and used to sample candidate points and one that is unrecognizable, which is pivotal for the acceptance probability (Chib and Greenberg 1995). MH algorithms, however, require the choice of a proposal density, which is used for drawing a candidate point which is then accepted or rejected based on a certain acceptance probability.

Frühwirth-Schnatter and Wagner (2006) and Frühwirth-Schnatter and Frühwirth (2007) developed the auxiliary mixture sampling for Poisson models, which allows for direct Gibbs sampling and hence, avoids Metropolis-Hastings steps. By utilizing auxiliary latent variables, a latent linear model is achieved. The distribution of the error terms of this latent model is approximated by a mixture of normal distributions.This procedure is based on data augmentation where the first step introduces unobserved inter-arrival times τ_{itj} for each observations y_{it} with $j = 1, ..., (y_{it} + 1)$. These inter-arrival times are independent and exponentially distributed with parameter μ_{ij}.

$$\tau_{itj}|\beta \sim exp(\mu_{it}) = \frac{\zeta_{itj}}{\mu_{it}}, \quad \zeta_{itj} \sim exp(1) \tag{3}$$

This method was then advanced by Frühwirth-Schnatter et al. (2009) where only two latent variables are used instead of $2(N + \sum_{i=1}^{N} y_i)$. These two latent variables are the arrival time τ^*_{it2} of the y_ith jump and the interarrival time τ^*_{it1} between the y_ith jump and the next one.

In order to estimate the augmented model, Frühwirth-Schnatter et al. (2009) formulate the prior distribution of τ^*_{it1} to follow an exponential distribution with mean $1/\mu_{it}$ and τ^*_{it2} follows a $\mathcal{G}(y_{it}, \mu_{it})$ distribution as defined in Bernardo and Smith (1994):

$$\tau^*_{it1} = \frac{\zeta_{it1}}{\mu_{it}}, \quad \zeta_{it1} \sim exp(1) \tag{4}$$

$$\tau^*_{it2} = \frac{\zeta_{it2}}{\mu_{it}}, \quad \zeta_{it2} \sim \mathcal{G}(y_{it}, 1) \tag{5}$$

Equation (4) and (5) can then be written as:

$$- log(\tau^*_{it1}) = log(\mu_{it}) + \epsilon_{it1} \tag{6}$$

$$- log(\tau^*_{it2}) = log(\mu_{it}) + \epsilon_{it2} \tag{7}$$

where $\epsilon_{it1} = -log(\zeta_{it1})$ and $\epsilon_{it2} = -log(\zeta_{it2})$.

In order for the nonlinear model to reduce to a linear Gaussian model, the densities of ϵ_{it1} and ϵ_{it2} are approximated by a mixture of R normal densities. ϵ_{it1} follows a Gumbel (extreme value type I distribution), which is approximated to a linear model by:

$$p(\epsilon) = exp(-\epsilon - e^{-\epsilon}) \approx \sum_{r=1}^{R} \omega_r f_N(\epsilon; m_r, s_r^2), \tag{8}$$

where $r = 1, ..., R$ and R gives the number of components. m_r is the mean and s_r^2 is the variance of the Gaussian distribution $N(\epsilon; m_r, s_r^2)$. ω denotes the weight. See Frühwirth-Schnatter and Frühwirth (2007) for an overview for the parameters (w_r, m_r, s_r^2) where R = 10. Since ϵ_{it2} follows a negative log-Gamma distribution and is approximating using the shape parameter ν as follows:

$$p_\epsilon(\epsilon; \nu) = \frac{exp(-\nu\epsilon - e^{\epsilon})}{\Gamma(\nu)} \approx \sum_{r=1}^{R(\nu)} \omega_r(\nu) \varphi(\epsilon; m_r(\nu), s_r^2(\nu)) \tag{9}$$

where the notation is similar as in equation (8) with $\varphi(\epsilon; m_r(\nu), s_r^2(\nu))$ indicating a Gamma density. However, the parameters (w_r, m_r, s_r^2) as well as the number of mixture components $R(\nu)$ now depend on ν. As the nonlinear model subsequently reduces to a linear Gaussian model Gibb's sampling methods can now be employed, see Frühwirth-Schnatter et al. (2009) for the exact sampling steps.

4.3 Introducing Variable Selection

Given the lack of theoretical guidance regarding the inclusion of various potential drivers of evictions and especially their time lag structure, we follow George and McCulloch (1993) introducing a Stochastic Search Variable Selection (SSVS) approach into the MCMC process for all variables but the COVID-19 Dummies, which are the main variables of interest and shall be included under all circumstances. To avoid over-parameterization the prior variance of a parameter i is set to $\psi_{1i}^2 = (10\hat{\sigma_i}^2)$ if the parameter should be included and to $\psi_{0i}^2 = (0.1\hat{\sigma_i}^2)$ if the parameter should be excluded from the model. σ_i is the standard error linked to the unconstrained least squares estimate of parameter i using panel corrected standard errors as suggested by Bailey and Katz (2011). By subsequently calculating the posterior inclusion probabilities, the relevance of each variable can be evaluated.

In principle, a fixed effects approach could be applied, which would see α_i being just another regression coefficient. Variable selection for the unit-specific intercepts could then simply follow the above procedure. However, there would always be an inbuilt information imbalance between some β_j and α_i as $\sum_{i=1}^{N} T_i$ observations are available to estimate β_j but only T_i observations for α_i, which makes the choice of a universal prior for all non-zero coefficients difficult. We thus follow Frühwirth-Schnatter and Wagner (2011) and use a shrinkage prior for the random intercept model: $\psi_{\alpha i}|Q \sim \mathcal{E}(1/(2Q))$, where ψ_{α_i} is the variance of the random intercept distribution, resulting in a Laplace random intercept model:

$$\alpha_i|Q \sim Lap(\sqrt{Q}) \tag{10}$$

which is sometimes also considered as a Bayesian Lasso random intercept model. Instead of simply fixing the scaling hyperparameter Q, we can again treat it as a random hyperparameter with prior $p(Q)$ turning the shrinkage prior for some α_i into a smoothing prior across all random intercepts:

$$Q \sim \mathcal{E}^{-1}(c_0, C_0/2) \tag{11}$$

The exact MCMC steps can be found in Frühwirth-Schnatter and Wagner (2011) as well as in the appendix of this paper.

5 Results

Table 2 gives an overview of the posterior summary[4]. It can be seen that most coefficients are significantly different from zero, and most of these show in the expected direction. For example, unemployment, as well as the lag of unemployment, have a positive effect on evictions. The same is true for the number of divorces and the size of the rental sector. As expected, a rise in the dependency ratio also results in an increase in evictions.

However, there appear to be some inconsistencies when looking at the coefficients and their lagged counterparts. While past rent prices exert a negative influence on evictions, current rent prices increase evictions. This is also the case for the number of low-wage households. This effect is reversed for income. Figure 2 shows the posterior inclusion probabilities for all variables but the interaction term. The variables with the highest inclusion probabilities are the dependency ratio, population, the number of divorces and its lag. The size of the rental sector and unemployment were included in 34 and 18 per cent of all iterations, respectively.

[4] We ran the MCMC with 10,000 iterations and a burn-in of 5,000.

To answer our main research question, namely, whether evictions have increased during the COVID-19 eviction policy, we included an interaction term between provinces and the year 2020. It can be seen that indeed evictions went down in all provinces, most notably in Salzburg[5].

The right plots in Figure 3 show the posterior density of all interaction terms. Again, it can be seen that the effect of the dummy is negative in all nine cases indicating that there was a significant decrease in evictions in 2020 in all provinces compared to pre-crisis values. Further, to check whether the MCMC chain properly represents the posterior distribution, trace plots are shown on the left side of Figure 3.

[5]Unfortunately, we do not have the data for 2021 for most variables, so we cannot test whether the number of evictions increased again in 2021.

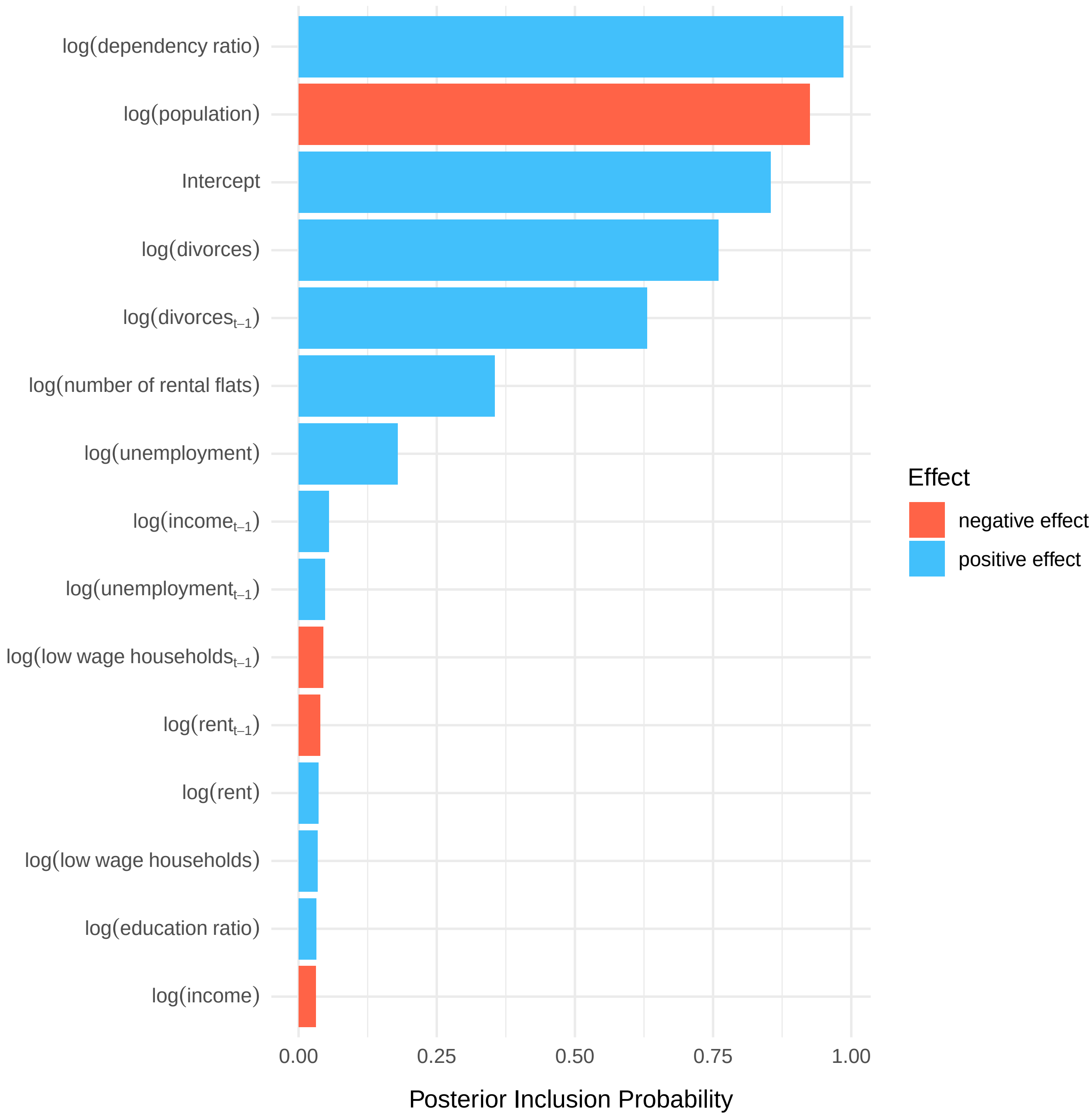

Figure 2: Posterior Inclusion Probabilities

Table 2: Posterior Summary

	5%	Median	95%
log(unemployment$_{t-1}$)	1.13	1.26	1.40
log(low wage count$_{t-1}$)	-0.57	-0.44	-0.26
log(divorces$_{t-1}$)	2.09	2.31	2.54
log(rent$_{t-1}$)	-0.30	-0.19	-0.07
log(income$_{t-1}$)	1.27	1.53	1.86
log(unemployment)	1.59	1.75	1.91
log(low wage households)	1.20	1.59	2.11
log(education ratio)	-0.02	1.00	1.03
log(dependency ratio)	4.90	6.61	8.96
log(divorces)	2.35	2.57	2.82
log(population)	-0.93	-0.89	-0.83
log(rent)	1.02	1.18	1.35
log(number of rental flats)	1.50	1.56	1.63
log(income)	-0.10	-0.07	-0.04
Burgenland :COVY	-64.45	-46.23	-22.03
Kaernten:COVY	-51.67	-43.37	-33.95
Niederoesterreich:COVY	-24.99	-16.17	-6.57
Oberoesterreich:COVY	-35.48	-27.52	-18.67
Salzburg:COVY	-58.02	-49.96	-40.37
Steiermark:COVY	-49.64	-38.28	-26.79
Tirol:COVY	-53.06	-43.94	-33.19
Vorarlberg:COVY	-54.75	-44.79	-32.32
Wien:COVY	-23.76	-18.81	-13.55
R^2	0.932		
Number of regions	85		
Years	11		

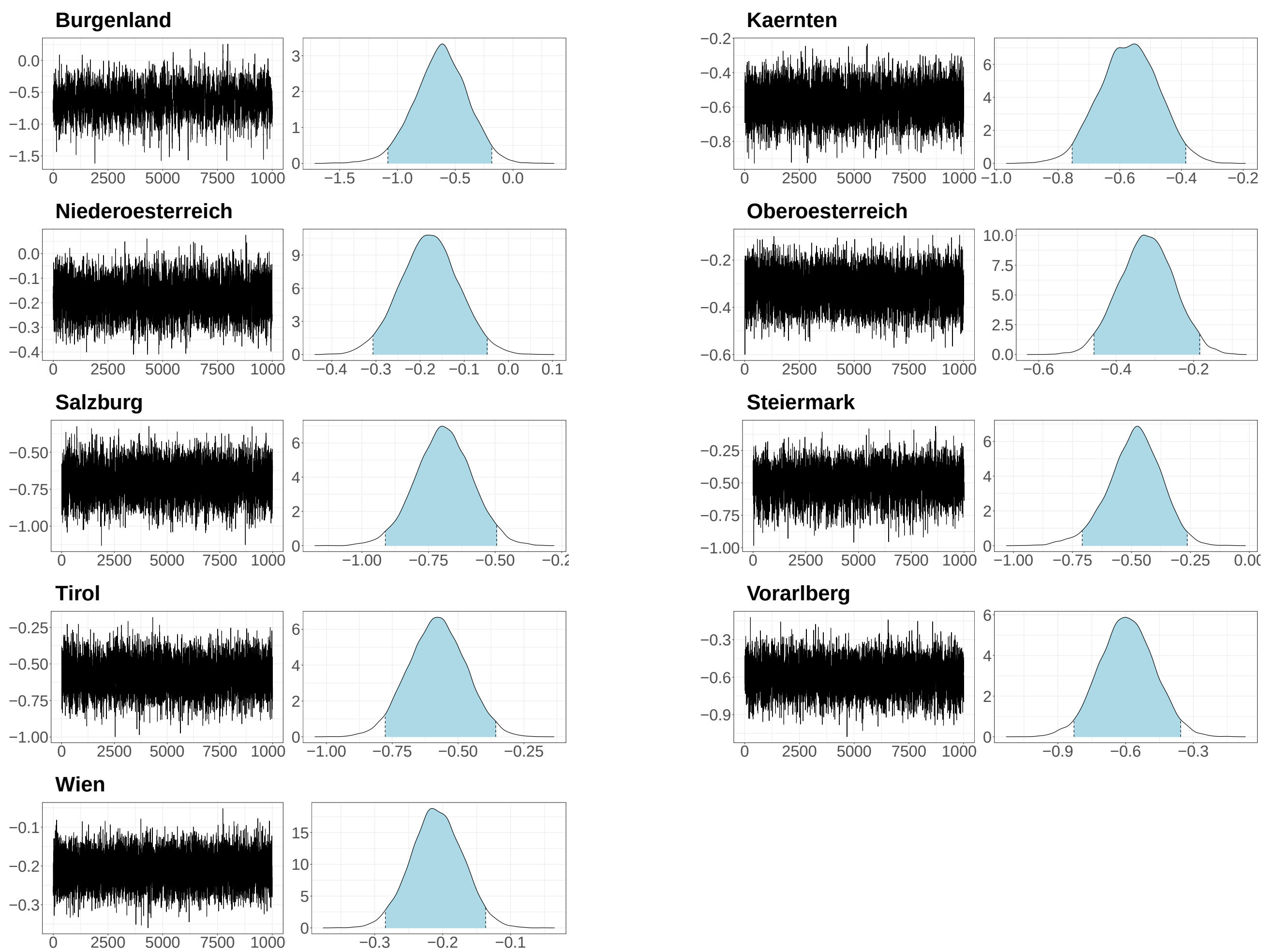

Figure 3: COVID-19 Dummies by Province

6 Conclusion

This paper investigates the efficiency of the COVID-19 anti-eviction policy in Austria. As unemployment rates and the share of people working short-time intensified drastically at the beginning of the pandemic, there was considerable concern that people might not be able to pay their rents which could significantly increase eviction rates. Hence, from April to July until December 2020, all Austrian provinces enacted policies which allowed for a deferral of rent payments with the aim of avoiding a rise in evictions during the pandemic. In addition, other measures, such as the possibility of prolonging rental contracts or a moratorium on evictions, were implemented.

By using panel data of evictions and other demographic and socio-economic variables of 85 Austrian districts, we analyze whether this policy reached its target of averting evictions. While there has been an overall decrease in evictions of approximately 1,100 from 2019 to 2020, it is not a priori clear whether this is due to the effect of the anti-eviction policy or other driving factors. Hence, a regression framework which acknowledges ceteris paribus interpretations needs to be employed. In order to test this, a Poisson Panel Model is utilized. We follow Frühwirth-Schnatter and Frühwirth (2007) and Frühwirth-Schnatter et al. (2009) who developed the advanced auxiliary mixture sampling for Poisson models. By introducing a Stochastic Search Variable Selection (SSVS) into the MCMC process, we further test which explanatory variables are most crucial for our model.

We find that the eviction policy has indeed contributed to a reduction of evictions in 2020. Although there are remarkable regional differences, evictions went down in all Austrian provinces. Yet, eviction rates in Vienna and Lower Austria declined the least while the reduction was highest in Salzburg and Burgenland, suggesting regional differences in eviction patterns and the efficiency of the policy. The next steps will be to include data for the year 2021 to evaluate whether evictions rose after the anti-eviction policy was lifted.

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Appendix

7 MCMC Steps

Selecting appropriate starting values for $\boldsymbol{\tau}$, $\boldsymbol{r}$ and $\boldsymbol{\mu}$ according to Frühwirth-Schnatter and Wagner (2006) as well as appropriate starting values for $\boldsymbol{\psi_\alpha}$ and Q according to Frühwirth-Schnatter and Wagner (2011) and repeat the following steps:

1. Sample the arrival and interarrival times $\boldsymbol{\tau}$ and the component indicators $\boldsymbol{r}$ conditional on $\boldsymbol{\beta, \alpha, \theta}$ and $\boldsymbol{y}$ for $i = 1, \ldots, N$ through following steps :

   (a) Sample $\varepsilon_i \sim \mathcal{E}(\mu_i)$. For $y_i = 0$, set $\tau^*_{i1} = 1 + \varepsilon_i$ and sample τ^*_{i2} from $Beta(y_i, 1)$ if $y_i > 0$ and set the corresponding $\tau^*_{i1} = 1 - \tau^*_{i2} + \varepsilon_i$

   (b) Sample r_{i1} from the following discrete distribution with $k = 1, \ldots, R(1)$

   $$p(r_{i1} = k|\tau^*_{i1}, \mu_i) \propto \omega_k(1)\varphi(-log(\tau^*_{i1}) - log(\mu_i; m_k(1), s^2_k(1))$$

   If $y_i > 0$ sample r_{i2} from the following discrete distribution where $k = 1, \ldots, R(y_i)$

   $$p(r_{i2} = k|\tau^*_{i2}, \mu_i) \propto \omega_k(y_i)\varphi(-log(\tau^*_{i2}) - log(\mu_i; m_k(y_i), s^2_k(y_i))$$

2. Sample $\boldsymbol{\beta}$ conditional on $\boldsymbol{\tau}$ and $\boldsymbol{r}$ through the following steps:

   (a) Define a multivariate observation vector $\tilde{\boldsymbol{y}}_{\boldsymbol{\beta}}$ of dimension $T(N_{y=0} + 2N_{y>0})$ where

   $$\tilde{y_{i\beta}} = \begin{cases} \begin{pmatrix} -log\tau_{i1} - m_{ri1} \\ -log\tau_{i2} - m_{ri2} \end{pmatrix} & \text{for } y_i > 0 \\ \begin{pmatrix} -log\tau_{i1} - m_{ri1} \end{pmatrix} & \text{for } y_i = 0 \end{cases}$$

   and a corresponding $\tilde{\boldsymbol{X}}$.

   (b) Then sample $\boldsymbol{\beta}$ from $\mathcal{N}(\boldsymbol{b_N}, \boldsymbol{B_N})$, where $\boldsymbol{B_N^{-1}} = \boldsymbol{B_0^{-1}} + \sum_{i=1}^N \tilde{\boldsymbol{x}}_{\boldsymbol{i}}{}' \tilde{\boldsymbol{x}}_{\boldsymbol{i}}/s^2_{ri}$ and $\boldsymbol{b_N} = \boldsymbol{B_N}(\boldsymbol{B_0^{-1}b_0} + \sum_{i=1}^N \tilde{\boldsymbol{x}}_{\boldsymbol{i}}{}' \tilde{\boldsymbol{y}}_{\boldsymbol{i}}/s^2_{ri})$

3. Sample $\boldsymbol{\alpha}$ conditional on $\boldsymbol{\tau}$, $\boldsymbol{r}$, $\boldsymbol{\psi_\alpha}$ and Q through the following steps:

   (a) Define a $1 \times T(N_{y=0} + 2N_{y>0})$ vector $\tilde{\boldsymbol{y}}_{\boldsymbol{\alpha}}$ where $\tilde{y}_{i\alpha} = \tilde{y}_{i\beta} - \tilde{\boldsymbol{x}}'_{\boldsymbol{i}}\boldsymbol{\beta}$

(b) Compute $B_i^{-1} = \frac{T_i}{s_{ri1}^2} + \frac{1}{\psi_i}$ for $i = 1, \ldots, N$

(c) Sample α_i from $\mathcal{N}(\sum_{t=1}^{T_i} \tilde{y}_{it} B_{it}, \frac{1}{2T_i} \sum_{t=1}^{T_i} B_{it})$ for $i = 1, \ldots, N$

4. Sample ψ_α conditional on α_i and Q from $\mathcal{GIG}(1/2, 1/Q, \alpha_i^2)$

5. Sample Q conditional on $\boldsymbol{\psi_\alpha}$ from $\mathcal{G}^{-1}(c_0 + N, C_N)$ where $C_N = C_0 + \frac{1}{2} \sum_{i=1}^{N} \psi_i$

6. For the SSVS, compute a two component mixture prior for β_i

   where $p(\beta_i|\omega, \theta) = (1 - \omega)p_{spike}(\beta_i|\theta) + \delta_i p_{slab}(\beta_i|\theta)$

   (a) Use a finite mixture for β_i according to $\beta_i|\omega, Q \sim (q - \omega)Lap(\sqrt{rQ}) + \omega t_{2\nu}(0, Q/\nu)$

   (b) Sample δ_i conditional on β_i using $Pr(\delta_i = 1|\psi_i, \omega, \theta) = \frac{1}{1+\frac{1-\omega}{\omega} L_i}$ where $L_i = \frac{p_{spike}(\beta_i|\theta)}{p_{slab}(\beta_i|\theta)}$

   (c) Draw ω from $\omega|\delta \sim \mathcal{B}(a_0 + n_1, b_0 + N - n_1)$ where $n_1 = \sum_{t=1}^{N} \delta_i$

7. Finally compute a new $log(\mu_{it}) = log(pop_{it}) + X'\beta + Z'\alpha$