Uneven Consequences of Coronavirus Pandemic: Evidence from a Real Time Survey

Ciftci, Muhsin

Goethe University Frankfurt

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Abstract. In this study, we investigate the impact of coronavirus pandemic on increased home office working, provision of payments to dependent employees on leave, and closed workplaces (voluntary or involuntary) of self-employed people using the online GESIS Panel survey on the Coronavirus SARS-COV-2 for Germany. To this end, we use the Bayesian estimation to measure the effects of a pandemic on key outcome variables, taking into account different levels of education, gender, household size, age, and the number of children below certain age of workers. Empirical results show that higher education level, gender, a larger household size, having children below the age of 12 significantly increase home office work. Men are more likely to work from home than women. On the other hand, women are more likely to get paid while on leave, and this could reduce the inequality documented by the existing research. A more striking result is that more educated workers, on average, are less likely to get paid while on leave. As for closed businesses, household size positively affects the number of voluntarily closed ones, and women are 20% more likely to experience having their business shut down by the authorities. A final remark is that more educated people are less likely to have their workplace closed by the authorities.

Keywords: Coronavirus, COVID-19, Germany, Employment, Bayesian

1 Introduction

Across the world, the coronavirus pandemic has brought about tremendous disruptions to the economy. Due to the precautionary measures meant to hamper the spread of the epidemic; the labor supply, either voluntary or involuntary, has declined sharply. Although the consequences of those policies differ for each country due to the institutional background and timing of the policy responses, a common result is an intense decline in the level of income and employment, Adams-Prassl et al. (2020). The labor market consequences of the pandemic, which pave the way to increasing inequality concerning gender, economic opportunities, and health vary across and within countries, Hipp and Bünning (2020), Collins et al. (2021), Van Dorn et al. (2020). To this end, we study the labor market outcomes of the pandemic in Germany using the online GESIS Panel Special Survey, conducted by Team (2020). We shed light on the sources and results of increasing tendency to work from home, continued wage payments as the workers are on leave for dependent employees. With regard to those who are self-employed, we further document the results for more working from home and closed businesses either voluntary or involuntary (by legal enforcement).

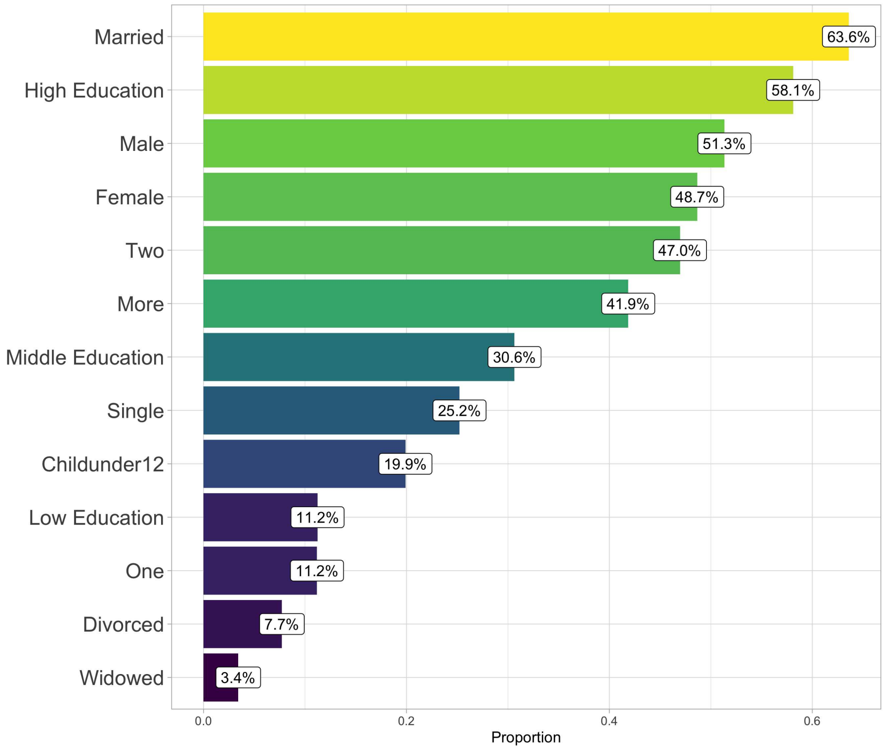
Since the beginning of the pandemic many countries around the world, including Germany, started implementing pro-labor policies. Rather than firing workers and reemploying them in response to the labor market shocks, firms reduced the working hours to adjust to the decline in labor demand. The so-called *Short Term Working* policy allows firms to reduce the hours worked per employee and hence prevent potential inefficiencies in the labor market stemming from the liquidity constraints, Adams-Prassl et al. (2020). The German short-term working policy allows to work a certain fraction of the usual time and the loss in income due to the decreased labor supply is compensated by the federal government agencies. The support is not limited to dependent employees. The federal government agencies further supported self-employed and small-scale businesses with one-time payments up to €9000 for three months. Against aforementioned labor market developments firms cut back the working hours per employee, switched to remote working due to health-related restrictions, and cut the wages either through the decline in working hours or interruptions in payments of workers on leave.

The degree to which people are affected by the economic policies and health-related restrictions varies across individuals due to personal characteristics such as gender, education level, marital status, age, whether there is a responsibility of childcare and household size. Existing research demonstrates that higher educated people are more likely to engage in remote working (Hoenig and Wenz (2021), Naumann et al. (2020)). On the contrary, less-educated workers are more likely to lose their jobs, experience income loss due to the reduction in hours worked, and thus get more disadvantageous. The pandemic has also amplified the inequality between men and women owing to the division of labor, such as child care and paid work, Czymara et al. (2021). The study of Holst et al. (2021) further documents that age, gender, employment status (fixed-term or part-time contract) plays a sizable role on the inequality.

Within this context, we contribute to the existing research concerning the effects of coronavirus pandemic (COVID-19) on the labor market outcomes in Germany. To this end, we make use of the Bayesian estimation to measure the effects on key categorical variables on labor market outcomes where we draw on the GESIS Panel survey on the Coronavirus SARS-COV-2 for Germany, conducted by Team (2020). In Bayesian estimation, we follow the Ghosh et al. (2018) to pinpoint the prior distributions for parameters of interest. We start the estimation process with specifying the prior values for parameters in logistic regression and combine them with the likelihood conditional on observed data. Unlike Maximum likelihood estimation (MLE), or frequentist estimation, we are also interested in the estimate of uncertainty around the parameters using normal-approximation techniques. The posterior distribution, which is proportional to our prior multiplied with the likelihood, is updated belief about the weights conditional on the observed data. We cannot directly evaluate the closed form of posterior distribution. Therefore we employ Markov Chain Monte Carlo (MCMC) sampling methods to approximate the posterior and obtain a distribution over the parameters.

Estimation results indicate that more home office is positively affected by higher education level, a larger household size, having children below the age of 12. Additionally, we find a crucial gender effect on more home office work, men are more likely to work from home than women. Empirical findings further show that women are more likely to get paid while on leave compared to men and this could reduce the inequality documented by the existing research. A more striking result is that more educated workers, on average, are less likely to get paid while on leave. The pandemic is likely to yield distinct repercussions for (dependent) workers with different education levels, gender, household size, and the number of children. On the other hand, many self-owned businesses are closed either voluntarily or involuntarily by the authorities during the pandemic. Among voluntarily closed ones, household size plays a crucial role. There are no marked differences among other variables, neither are they statistically significant when we take the probability of directions into account. For workplaces closed by the authorities, women are approximately 20% more likely to experience having their business shut down temporarily. This could increase gender inequality. Finally, more educated people are less likely to have their workplace closed by the authorities. These findings, together with the aforementioned ones, could have important consequences for people with different levels of education, gender, household size, and children below a certain age.

Figure 1: Percentage of Each Category in the Sample

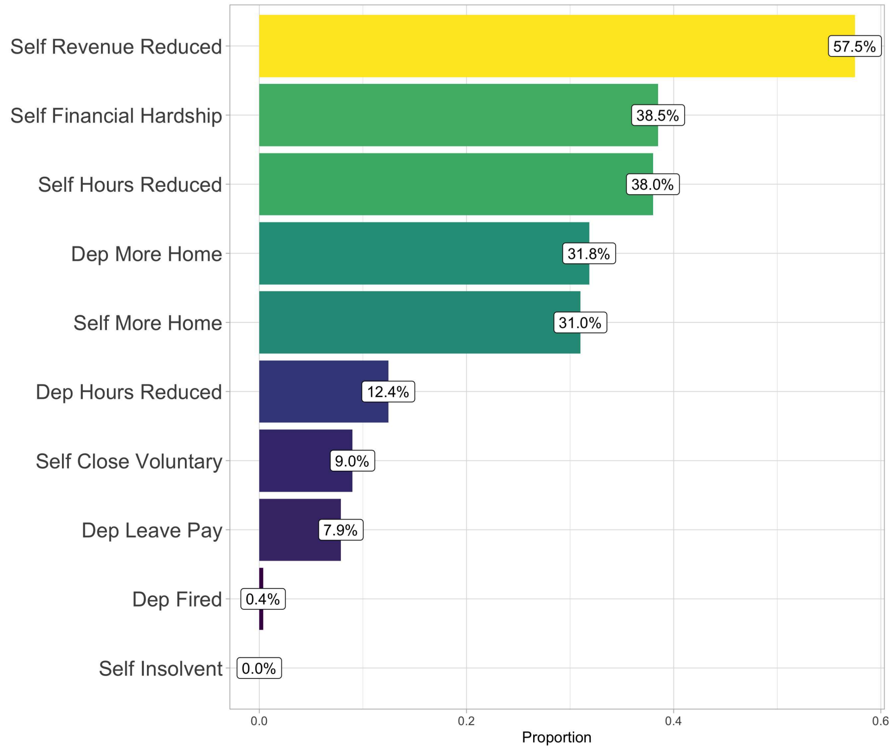


2 Data

In this study, we make use of the data from the GESIS Panel survey on the Coronavirus SARS-COV-2 for Germany, conducted by Team (2020). The data are cross-sectional, and the variables are categorical. For this reason, we are not able to compare the change in behavior of respondents over time. The survey is conducted online with a non-random sample and therefore it does not necessarily reflect the responses of the entire German population. For each categorical variable we construct respective dummies. The key variables used in this study are education, sex, marital status, whether the respondents have children under the age of 12, household size. For outcome variables we use whether respondents get paid while on leave, whether they use more home office, and whether there is a job loss or temporary leave of job for self-employed workers.

Within the sample, the proportion of respondents across different categories is uneven. 11.2% of the respondents have low education, 58.1% have high education, and the remaining people have middle education (Figure 1). Regarding the marital status, 64% are married, 25% are single, 8% are divorced, and 3% are widowed. On the other hand, the proportion of men (51%) and women (49%) are rather close to each other. Among the respondents, only 20% have children below the age of 12. Another key variable, household size, shows that approximately 11.2% of the sample has at the most

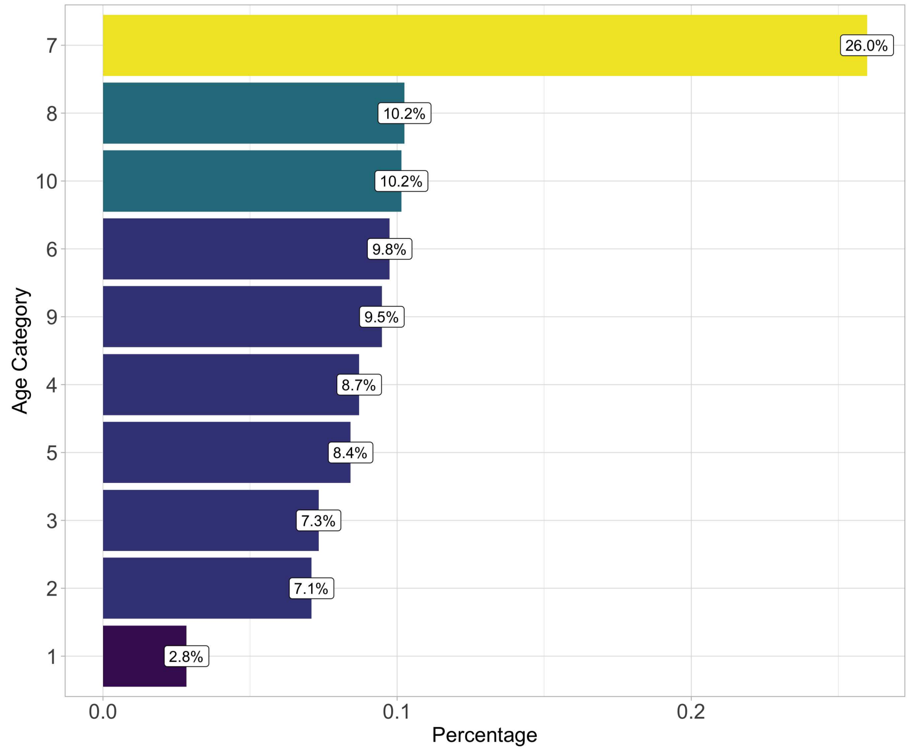
Figure 2: Percentage of Outcome Variables in each Respective Group



household size of 1, 47% of the sample respondents has the household size of two and the remaining 42% has a household size larger than that.

Out of the entire sample the majority of respondents are dependent employees, only 200 of them are self-employed. 31.8% of the dependent employees and 31% of the self-employed people work more from home, (Figure 2). Out of dependent employees, 12.4% have reduced working hours due to the Short Time Working scheme, 7.9% get a payment while on leave and an ignorable percentage is fired. On the self-employed side, we witness a more dramatic picture that 57.5% reports a decline in revenues, 38.5% facing financial hardship, 38% has reduced working hours, 9% closed their business voluntarily for a temporary period. Finally, we show the percentage of ten different age categories, youngest being 1 (less than 25 years old) and 10 being the oldest (more than 71 years old), (Figure 3). The youngest (2.8%) are underrepresented and those who are between age 51 and 60 are overrepresented (26%). The remaining age groups rather show a homogeneous profile.

Figure 3: Percentage of Age categories



3 Bayesian Logistic Regression

The binary regressions for a set of N observations, $y = (y_1, y_2, ...y_N)$, are expressed as

$$P(y_i = 1|x_i, \beta) = F_\varepsilon(x_i\beta)$$

where $F_\varepsilon(x_i\beta)$ is the cumulative distribution function (cdf). Under this representation, we employ the logistic distribution for cumulative distribution function (cdf) $F_\varepsilon(\varepsilon) = \frac{exp(\varepsilon)}{1+exp(\varepsilon)}$. This will result in *logit* model;

$$P(y_i = 1|x_i, \beta) = G(x_i\beta) = \frac{exp(x_i\beta)}{1 + exp(x_i\beta)}$$

where we use $G(z)$ for *link* function. Since the probability of y_i given the data is

$$[G(x_i\beta)]^{y_i}[1 - G(x_i\beta)]^{1-y_i}$$

then the likelihood of N observations will be

$$\mathcal{L} \equiv \Pi_{i=1}^{N}[G(x_i\beta)]^{y_i}[1 - G(x_i\beta)]^{1-y_i}$$

where the parameters are optimized over the likelihood. After setting up the cumulative distribution function, we use logistic regression to estimate the likelihood of each outcome variable conditional on the set of explanatory variables.

A second step in the Bayesian estimation is to specify the prior values for parameters and combine them with the likelihood. Unlike Maximum likelihood estimation (MLE), we are also interested in the estimate of uncertainty around the parameters using normal-approximation techniques. We start with prior information for parameters in logistic regression following Ghosh et al. (2018). We assign *Cauchy Priors* for the parameters in the logistic regression with appropriate location and scaling values. The posterior distribution, which is proportional to our prior multiplied with the likelihood, is updated belief about the weights conditional on the observed data.

$$f(\mu,\sigma^2|X) \propto f(X|\mu,\sigma^2)f(\mu,\sigma^2)$$

where $f(\mu,\sigma^2|X)$ is the posterior distribution, $f(X|\mu,\sigma^2)$ is likelihood and $f(\mu,\sigma^2)$ is the prior distribution. We cannot directly evaluate the closed-form of the posterior distribution. As a solution, we use Markov Chain Monte Carlo sampling methods to approximate the posterior and obtain a distribution over the parameters.

4 Findings

4.1 More Working from Home

In this section we provide the empirical findings for each respective outcome variable. Figure 4 shows the posterior distributions for each parameter in Bayesian logistic regression for more home working. Prior values for parameters follow from Ghosh et al. (2018). We use 25000 draws for posterior distribution and burn first 10% of the draws to mitigate the effects of initial observations. Posterior density estimates for parameters in the logistic regression indicate that while variables such as education level and household size (two or more than two) have a positive impact on more home working, being female and not having children below the age of 12 have a negative effect. All parameters except the intercept are quite likely to lie in the interval between 0 and 2.5 in absolute value since most of the posterior distribution mass lies between these values. In other words, based on our prior knowledge and the observed data, we are highly confident that posterior parameter estimates lie between *Credible Intervals*, which are often used to denote the confidence intervals in Bayesian terminology.

Contrary to the linear models, density estimates of coefficients does not indicate the marginal effects due to the nonlinear structure of logistic regression. To quantify

Figure 4: Posterior Distribution of Parameters (More working from Home, Dependent Employees)

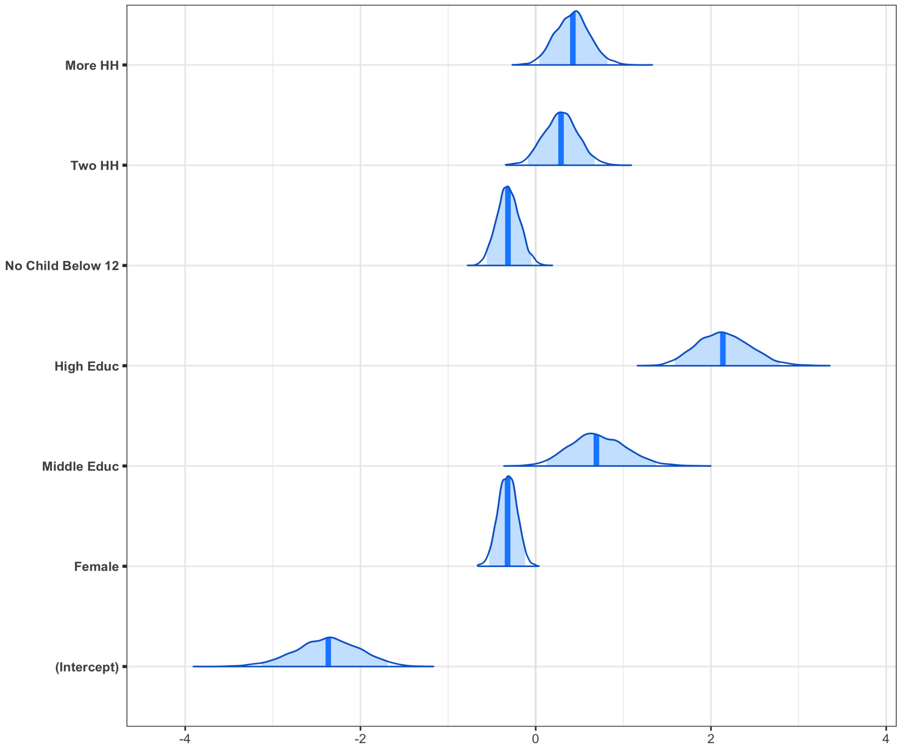


Figure 5: Marginal Effects (More working from Home, Dependent Employees)

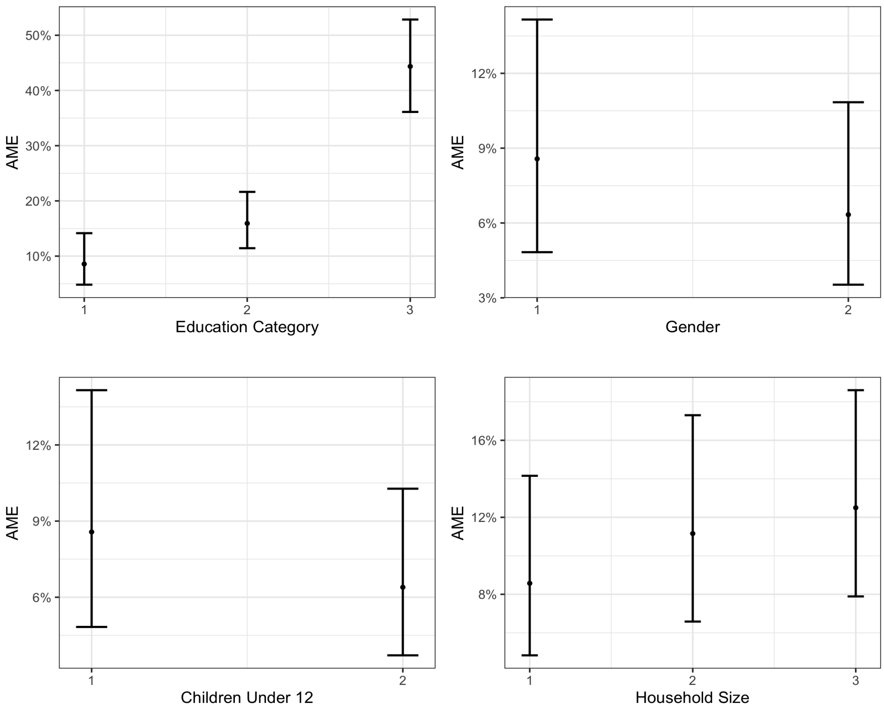
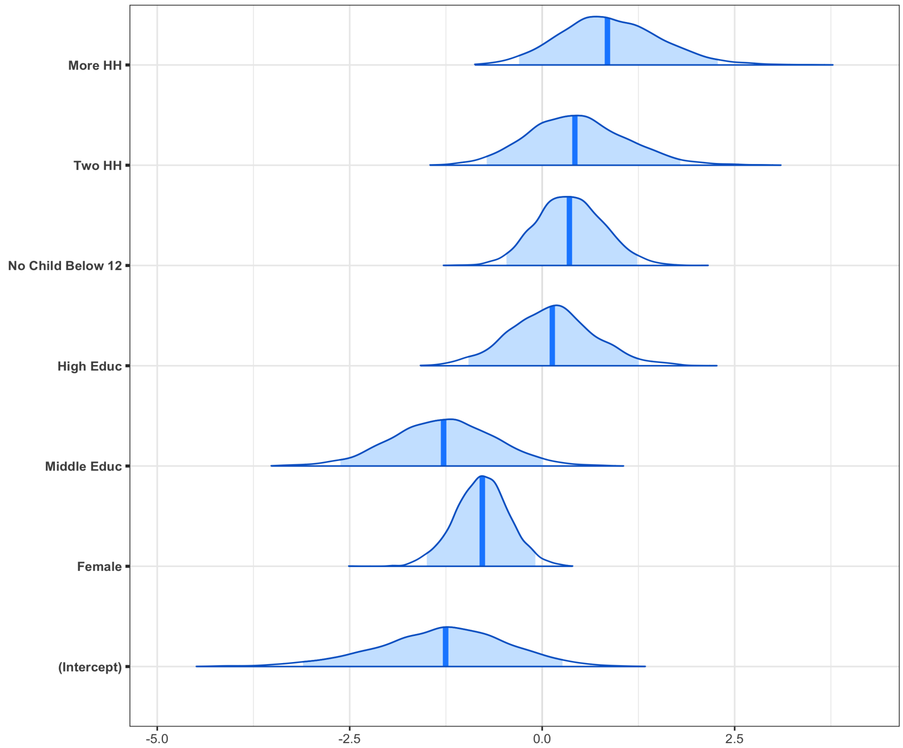


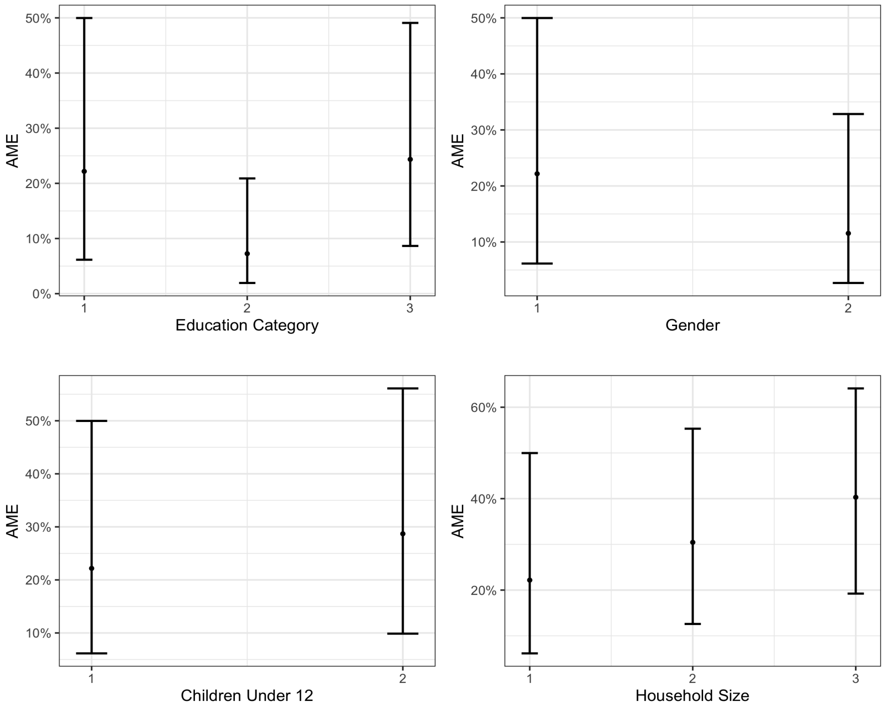
Figure 6: Posterior Distribution of Parameters (More working from Home, Self Employed)



the impact of each variable on the probability of more home working we resort to the marginal effects, Figure 5. Marginal effects for different categories in education (1 is the lowest and 3 is highest) demonstrate that more educated people are more likely to work from home than the less educated. On average, those who have high education have a probability of approximately 43 percent to work more from home, while the respective probabilities for people with an intermediate and low level of education are 15 and 10 percent. The results point to a significant difference in probabilities of more home working in regard to the level of education attained, further supporting the results of Hoenig and Wenz (2021). In regard to the gender dynamics, men (1) are more likely to work from home than women (2) (by 2%) since most of the essential workers in Germany are women, Hipp and Bünning (2020). On the other hand, those who have children under the age of 12 are more likely to work from home due to childcare. Workers without children under 12 have more flexibility, no burden for childcare, and thus are more likely not to work from home.[1] Finally, the size of the household is also significant in determining the more working from home. Clearly, as the household size increases the tendency toward homework goes up as well.

[1] In the original dataset, male and female are denoted by 1 and 2 respectively. Having children below the age of 12 is denoted by 1, the opposite is by 2. To keep the results compatible with the original data set, we leave the variables as they are, instead of converting them to 1 and 0.

Figure 7: Marginal Effects (More working from Home, Self Employed)



4.1.1 Probability of Direction

One challenging issue in Bayesian estimation is that we are not able to directly measure whether the estimated coefficients are statistically significant or not. We rather refer to the *probabillity directions*, Makowski et al. (2019) such that one and two-sided significance levels for p-values can be calculated as;

$$
\begin{aligned}
pvalues_{one-sided} &= 1 - p_d \\
pvalues_{two-sided} &= 2 * (1 - p_d)
\end{aligned}
$$

where p_d refers to the probability of direction which is an index of effect existence, ranging between 50% to 100%. Corresponding probability directions (Table 1) of more working from home for dependent employees shows that all coefficients except that of middle education are statistically significant. For self-employed workers, only gender and education play a statistically significant role.

Our results are compatible and further support the findings of the existing research. The fact that education and gender are significant factors in explaining the home office work is further documented by Adams-Prassl et al. (2020), Hipp and Bünning (2020), Hoenig and Wenz (2021), Czymara et al. (2021). We further validate these results, taking the parameter uncertainty and prior knowledge into account. Additionally, we contribute to those studies by incorporating the effects of household size and having children below the age of 12, which requires a considerable amount of child care.

Another point worth mentioning is whether self-employed workers are working more from home compared to the pre-pandemic situation. In line with the findings of the dependent employees, men are more likely to work from home than women. People in the highest level of education category are more likely to work from home than those who have a lower level of education level. The larger is the household size, the more likely is it to work from home, Figure 6 & Figure 7. However, in this case, results are not as sharp as for the dependent employees. The sample of self-employed people contains only 200 individuals and is less representative compared to that of dependent employees.

4.2 Getting Paid while on Leave

Getting paid while on leave is another significant issue faced during the times of epidemic. Many more businesses are closed either voluntarily or by legal enforcement throughout the whole country and this, in turn, triggers a cut in wages or in payments for those who are temporarily on leave. Due to the decline in revenues and profit margins of the businesses, dependent workers are likely to experience reductions in either wages or payments they receive while on leave. Under this case, surprisingly, we find that women are systematically more likely to get paid while on leave than men, Figure 8 & Figure 9. On average women are 5% more lucky to get paid compared to men. Probability directions, parameter densities, and marginal effects together support this argument. On the other hand, coefficients of density point out that education makes it less likely to get paid while on leave. This could stem from the fact that most of the less educated people are essential workers at the same time, and those essential workers are more likely to experience a continued payment while on leave. Probability directions (or corresponding p-values) are statistically significant only for education and gender. We do not find any supporting probability direction for household size and having children below the age of 12.

Figure 8: Posterior Distribution of Parameters (Getting Paid while on Leave)

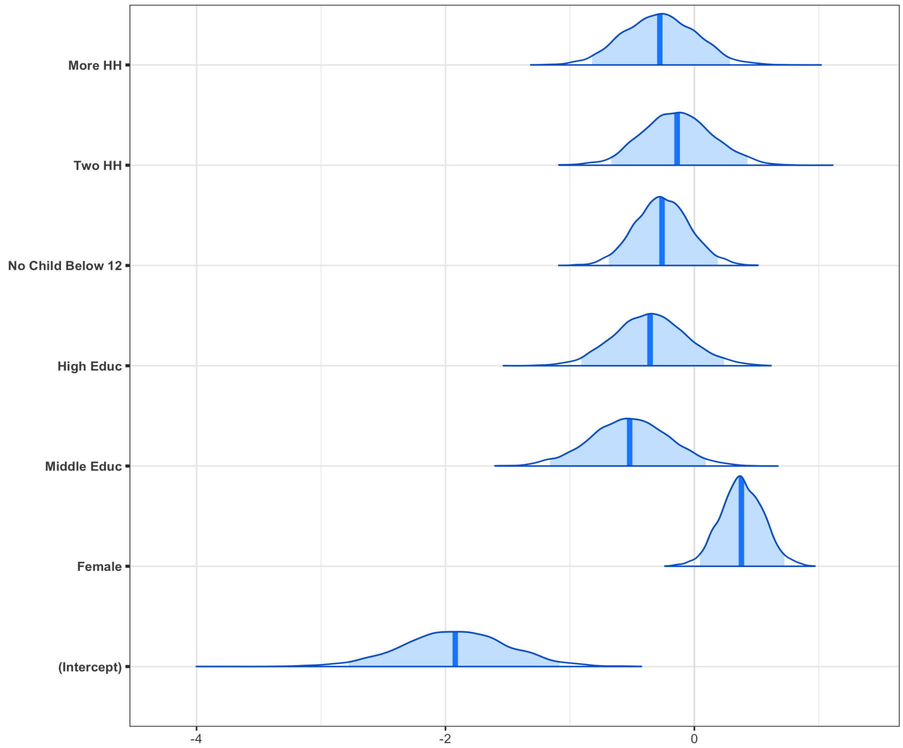


Figure 9: Marginal Effects (Getting Paid while on Leave)

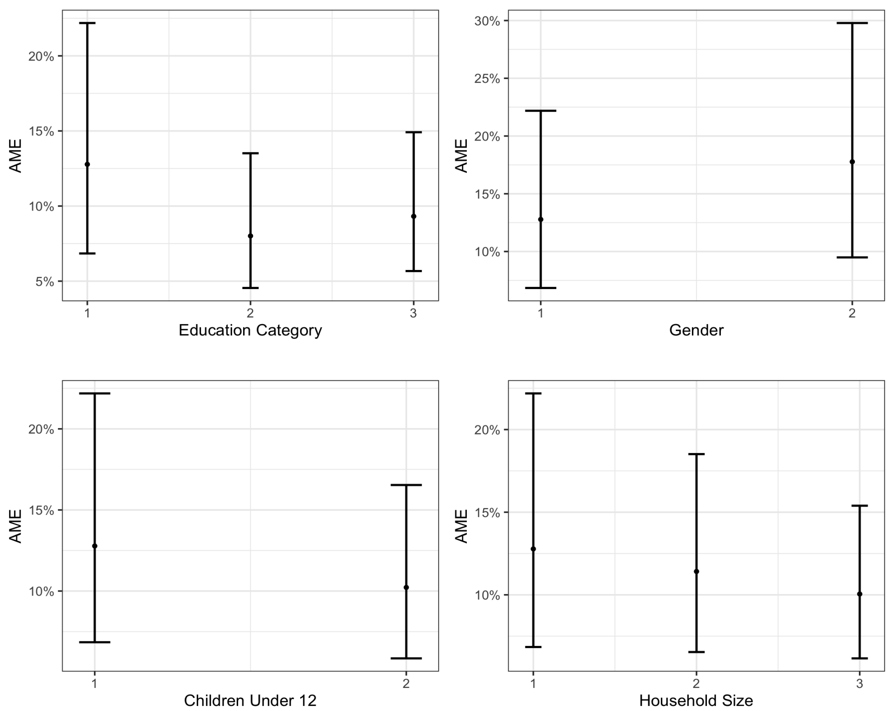
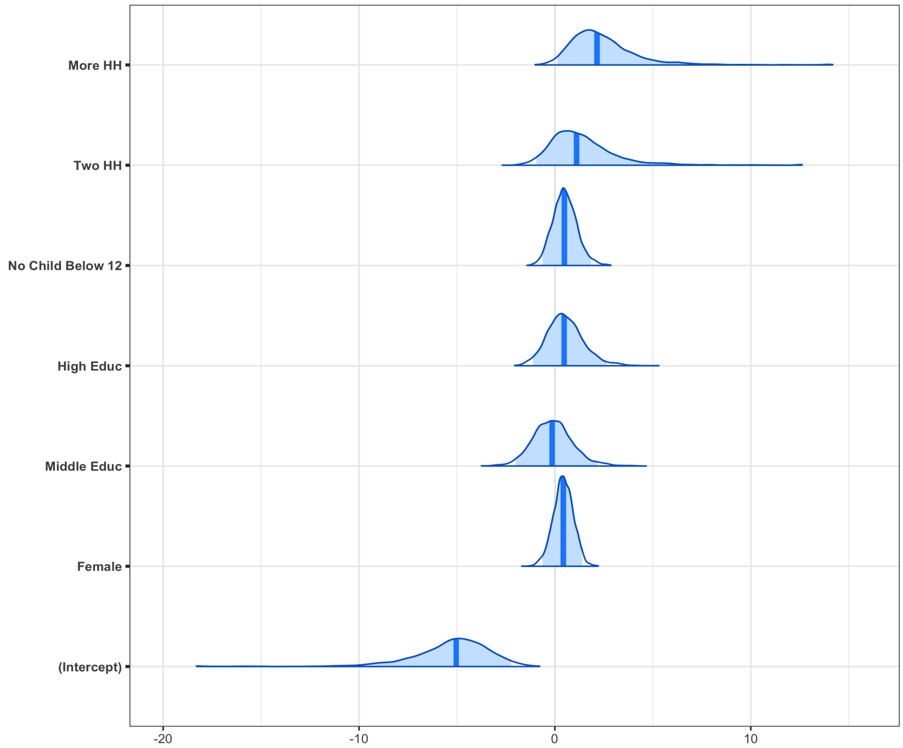


Figure 10: Posterior Distribution of Parameters (Voluntarily Closed Businesses)

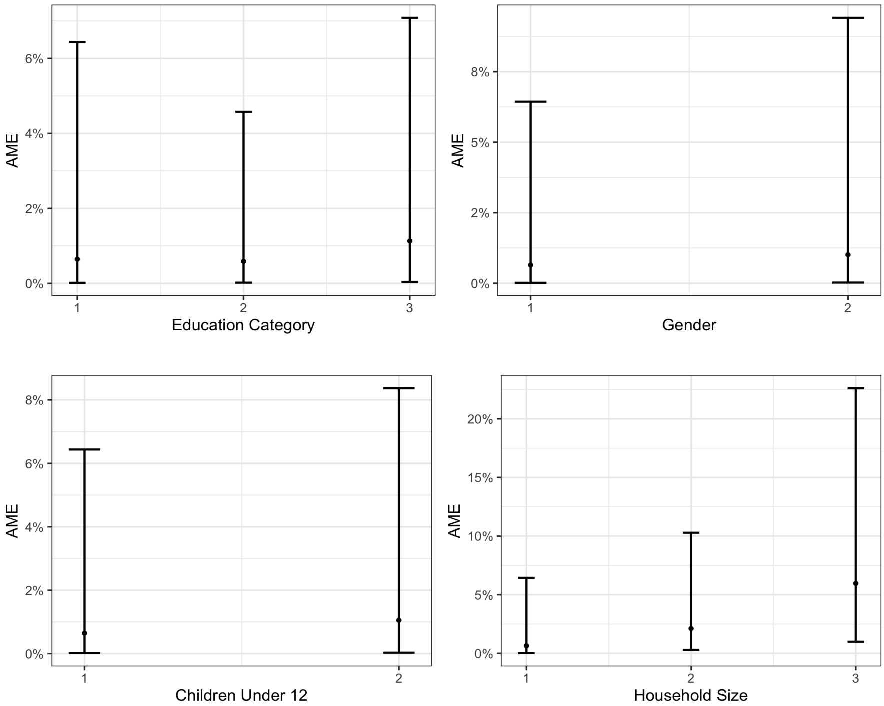


4.3 Closed Businesses

The coronavirus not only affected the way people work, either from home or the office, but also left many people unemployed, triggered the shutdown of the myriad of self-owned businesses. Self-owned businesses are shut down either by the owners voluntarily or by legal enforcement. The local law across German states is different and the measures taken during the pandemic and their timing varies might as well. This in turn paves a way for a different economic environment at the local level. Among the voluntarily closed businesses, there is a rather homogeneous profile that key variables such as gender, education level have close marginal effects. On the other hand, the size of the household plays a significant role. A larger household size affects the voluntary close of businesses positively. The posterior distribution of more households is positive, marginal effects indicate that those who have a household size larger than 2 are approximately 5% more likely to close their businesses voluntarily. This result could stem from the contagion effect of the pandemic.

On the other hand, some self-owned workplaces are closed by the authorities temporarily. The posterior distributions, marginal effects, and the corresponding probability directions show that women are more likely to experience shut down of their business than men. On average women are 20% more likely to have their workplace closed by the authorities than men. This could increase the inequality between women and men, as documented by Hipp and Bünning (2020). Another crucial point is that more

Figure 11: Marginal Effects (Voluntarily Closed Businesses)



educated people are less likely to close their workplace by the authorities. The posterior distributions and marginal effects support this result. On average more educated people are less likely to close their businesses compared to the less educated people. These results could further create more inequality due to the potential decline in the income of less-educated people.

Figure 12: Posterior Distribution of Parameters (Closed Businesses by Authorities)

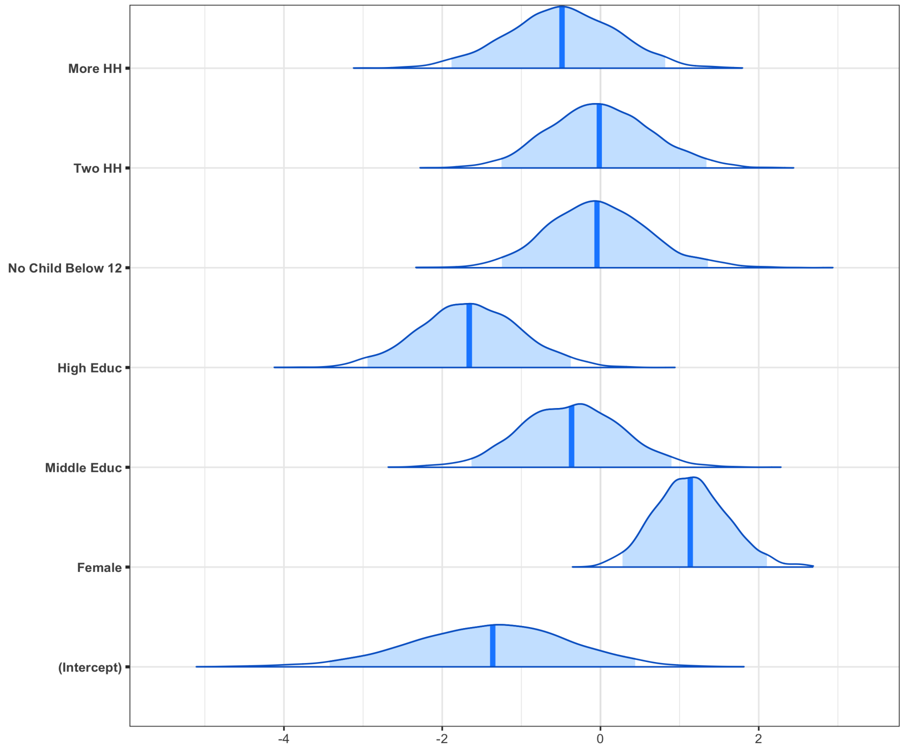
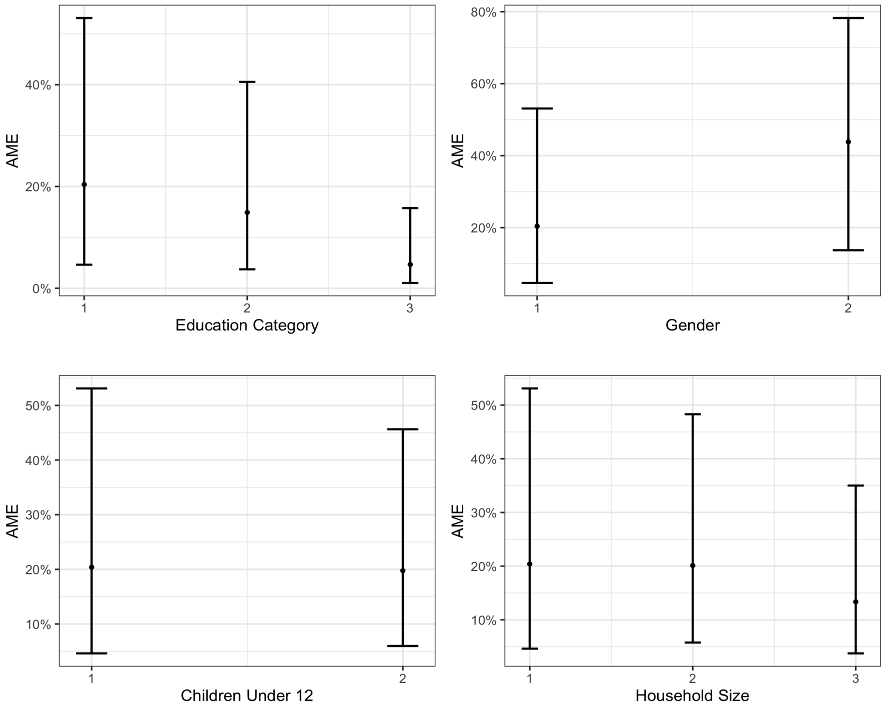


Figure 13: Marginal Effects ((Closed Businesses by Authorities)



5 Conclusion

In this paper, we studied the impact of the coronavirus pandemic on the key outcome variables for Germany, using an online survey conducted by Team (2020) in 2021. In the empirical estimations, we made use of logistic Bayesian estimation since we are not only interested in the mean values for parameter estimates but also attach importance to uncertainty around the parameters. We further made use of the marginal effects for inference in the logistic regressions, since the coefficients cannot be interpreted the usual way due to the nonlinearity of the *link* function. Empirical results show that more home working (home office) is positively affected by higher education level, a larger household size, having children below the age of 12. Furthermore, men are more likely to work from home than women. On the other hand, women are more likely to get paid while on leave compared to men and this could reduce the inequality documented by the existing research. A more striking result is that more educated workers, on average, are less likely to get paid while on leave. Another crucial point is that many self-owned businesses are closed either voluntarily or involuntarily. Among voluntarily closed workplaces, household size plays a significant role. There are no marked differences among other variables, neither are they statistically significant when we take the probability of directions into account. As for workplaces closed by the authorities, women are 20% more likely to experience having their business shut down. This could increase gender inequality. A final finding is that more educated people are less likely to have their workplace closed by the authorities. These results together with the aforementioned ones can have important consequences for people with different levels of education, gender, household size, and children below a certain age.

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Appendix

Table 1: Probability Directions for All Models

	Parameter	Model 1	Model 2	Model 3	Model 4	Model 5
1	Constant	1.00	0.95	1.00	1.00	0.93
2	High Education	1.00	0.59	0.89	0.72	0.99
3	Female	1.00	0.99	0.98	0.80	1.00
4	Middle Education	0.99	0.97	0.95	0.56	0.72
5	No Child below 12	0.99	0.80	0.88	0.80	0.53
6	More Househollds	0.99	0.92	0.82	0.98	0.76
7	Two Households	0.93	0.76	0.69	0.83	0.51