INSTITUTE FOR EMPLOYMENT RESEARCH
The Research Institute of the Federal Employment Agency

IAB-DISCUSSION PAPER

Articles on labour market issues

10|2021 Lockdown length and strength: labour-market effects in Germany during the COVID-19 pandemic

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ISSN 2195-2663

Lockdown length and strength: labour-market effects in Germany during the COVID-19 pandemic

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Abstract

This paper evaluates the short-term labour market impact of the COVID-19 containment measures in Germany. It examines two dimensions of the first lockdown in Germany, namely the length and the strength of the lockdown. While the assessment of the length is conducted via variation across regions and time in closing days and curfews, the latter uses the degree of closure in different sectors. For the length of the lockdown we find that an additional day of closure lead to an increase in the separation rate of 2.7 percent and a decrease in the job-finding rate of 1.8 percent. For the strength of the lockdown the results show that a higher degree of closure increases separations and lower job findings to a similar extent. In both dimensions, we find that the effects are non-linear over time. Given this approach, we find that 31 percent of the considerably increased inflows from employment into unemployment, and 33 percent of the reduced outflows from unemployment to employment in the first wave were due to the treatment effect of the lockdown measures. In sum, the lockdown measures increased unemployment in the short run by 80,000 persons.

Zusammenfassung

Dieses Papier evaluiert die kurzfristigen Arbeitsmarkteffekte der COVID-19-Eindämmungsmaßnahmen in Deutschland. Wir untersuchen zwei verschiedene Dimensionen des ersten Lockdowns in Deutschland, nämlich die Länge und die Stärke des Lockdowns. Während die Länge über die regionale und zeitliche Variation der Schließungstage und Ausgangssperren erfolgt, wird für die Stärke der Grad der Schließung in verschiedenen Branchen herangezogen. Für die Länge des Lockdowns finden wir, dass ein zusätzlicher Tag zu einem Anstieg der Entlassungsrate um 2,7 Prozent und einem Rückgang der Einstellungsrate um 1,8 Prozent führt. Für die Stärke der Schließung zeigen die Ergebnisse, dass ein höherer Grad der Schließung die Entlassungen erhöht und die Einstellungen in ähnlichem Ausmaß senkt. In beiden Dimensionen stellen wir fest, dass die Effekte im Zeitverlauf nicht linear sind. Mit diesem Ansatz finden wir, dass 31 Prozent der deutlich erhöhten Zuflüsse aus Beschäftigung in Arbeitslosigkeit und 33 Prozent der verringerten Abflüsse aus Arbeitslosigkeit in Beschäftigung in der ersten Welle auf die Schließungsmaßnahmen zurückzuführen sind. In Summe erhöhten die Eindämmungsmaßnahmen die Arbeitslosigkeit in der kurzen Frist um 80.000 Personen.

JEL

J6, E24

Keywords

Keywords: containment measures, COVID-19, job finding rate, separation rate

Acknowledgements

We thank Maximilian Studtrucker and Katharina Vogel for excellent research assistance. Furthermore we thank participants of the 17. IWH/IAB-Workshop, the DTMC COVID-19 Workshop 2020 and the RWI research seminar for valuable comments and suggestions.

1 Introduction

In 2020, the Corona virus started to spread across the globe. All over the world governments reacted by shutting down the economies. Now, in the beginning of 2021, the pandemic is still ubiquitous,and though vaccines exist, a lot of countries faced a second or even third shutdown over the course of the fall and winter. Meanwhile a lot is known so far about the reactions of the economies on the containment measures. The literature, that emerged so far, combines the epidemiologic workhorse model, the so-called SIR-model with different labor market models (see Kapicka and Rupert (2020), Bradley, Ruggieri and Spencer (2020) or Birinci et al. (2020)). This kind of literature is helpful in determining how an optimal policy should look like and gives indication which kind of policy would help to balance out inequalities that arise through the containment measures. However, the policy that actually takes place might be a very different one. Empirical papers are helpful in this respect as they allow to observe true outcomes of this pandemic.

In this paper we contribute to the existing literature by examining two different dimensions of a lockdown, namely the length and the strength. The data allows to disentangle the effects on hirings, separations and short-time work, the major German job retention scheme. These outcomes are observed from February to August 2020, to not just cover the drop but also the effect of the recovery. To analyse the length of the lockdown we exploit a detailed regional data set on containment measures in Germany (Bauer and Weber 2020) that allows to track the duration of economic closure by sector. Methodically we take advantage of the fact that the containment measures were implemented by the German state governments at different times and not uniformly nationwide. The resulting regional variation in the introduction and termination of the measures allows us to estimate the direct effect of a varying length of lockdown on local labor market outcomes. Given this setup, we run weighted fixed effects regressions. To examine the strength of the lockdown, we use the degree of closure in each industry sector. The information we use to measure the degree of closure is based on the estimated loss of input. In the estimation we rely on random-effects models in which we assess the effects for each point in time separately.

This paper complements potential research designs using the international dimension (e.g. Sazmaz et al. (2021), Tetlow et al. (2020)), which may benefit from larger data variation. In contrast, the underlying approach has advantages such as comparable epidemiological conditions and institutional regulations. For instance, due to homogenous school systems and social infrastructure, similar cultural events, and a uniform standard of living across the German federal states one can expect the implemented policy measures to exhibit a comparatively similar impact on the cross-sectional observations.

The most related papers to ours are from Betcherman et al. (2020) and from Juranek et al. (2020). The first paper uses a difference-in-difference approach to assess the impact of a layoff restriction intervention and finds that especially hampered hiring is causing the increase in unemployment in Greece, the second paper evaluates different policy styles in a cross-country study of Scandinavia and finds that Sweden only faced a minor labor market reaction. Bauer and Weber (2020) examined the effects of the containment measures on the job-finding and separation rate, however, the data was very limited at that point of time. In comparison to these papers, our uses comprehensive data and allows for a thorough research design, e.g. better control of time-invariant differences across region using panel regressions. Furthermore this paper allows to better disentangle the effects of length and strength of the lockdown.

The findings are the following: For the length of the lockdown we find that an additional day of closure lead to an increase in the separation rate of 2.7 percent and a decrease in the job-finding rate of 1.8 percent. For the strength of the lockdown the results show that a higher the degree of closure, increase separations and lower job findings to a similar extent.

In a back-of-the-envelope calculation, we find that 31 percent of the considerably increased inflows from employment into unemployment, and 33 percent of the reduced outflows from unemployment to employment in the first wave were due to the treatment effect of the lockdown measures. This increased unemployment in the short run by 80,000 persons.

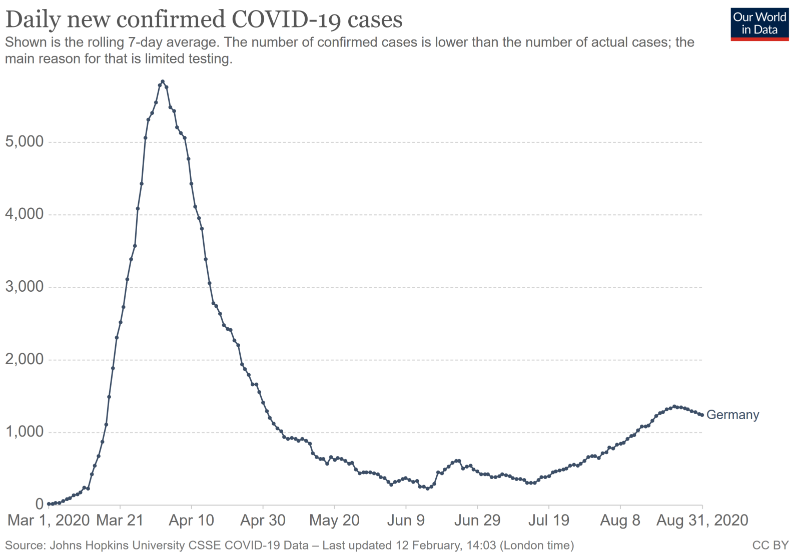
In general, economic closures impact unemployment flows and short-time work more strongly than curfews. Both, separations and job findings are affected. We find non-linearities in the regressions, which point to two facts. First, further days of closure are less important once the lockdown already started. Second, the lasting hiring weakness after the lockdown is not specific to lockdown sectors.

While Section 2 presents some facts about the events during the Covid-19 pandemic in Germany, section 3 and 4 display our regression exercise. Section 5 is highlighting the effects on short-time work. Section 6 provides robustness checks. Section 7 concludes.

2 Germany in the first wave of the pandemic

On January 27th 2020 the first infection with the Covid-19 virus was detected in Germany. Initially, the pubic authorities kept the spread of the virus under control by tracking the infection chain. Nonetheless, in February and March, the infection numbers started to increase rapidly (see Figure 1). In mid march, the German government decided to take action. A lockdown was imposed from mid March to mid April. Travel was restricted, schools and child care were closed, and also retail.

Figure 1: Daily number of confirmed cases over time



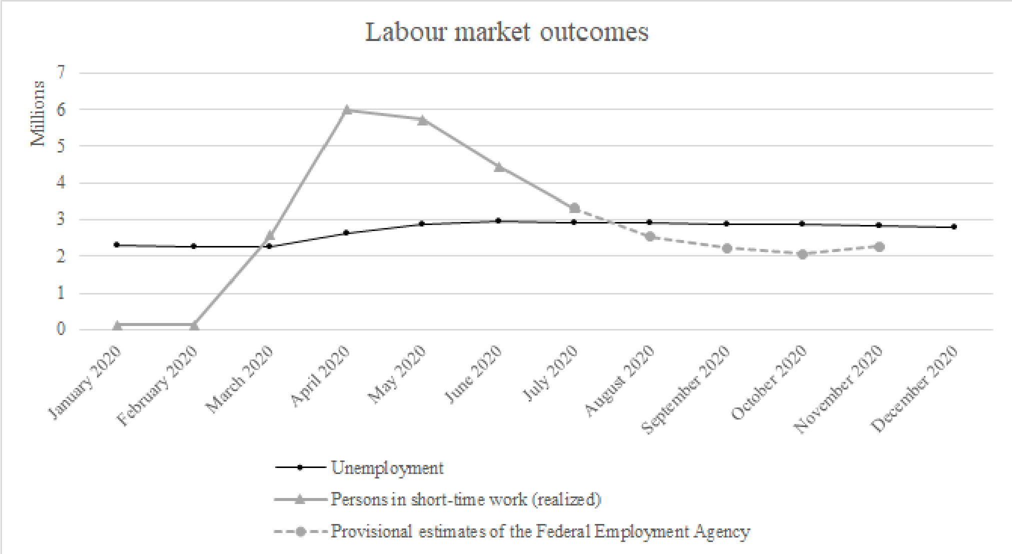
Source: COVID-19 Data Repository by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University.

While this policy was effective in reducing the infection numbers, it also caused distortions in the economy (e.g., Weber, 2020). In April and May, the numbers of notifications for short-time work, the German job retention scheme, rocketed. But also unemployment increased severely. Figure 2 shows both outcomes.

Over the summer, the situation relaxed. Short-time work and unemployment started to decrease, though did not reach the pre-recession level. In fall, the rate of infection started to increase again, and a second lockdown followed. While the effect on the infections can be easily tracked in real time. The reaction on the labour market is still ongoing and will be revealed with a time delay. As it will take time to vaccinate the population because vaccine is limited, there is a possibility, that we will have to have a lockdown every now and then.

In the light of these considerations, the question that naturally arises as labor economist is which effects the strength and the length of a lockdown exhibits in terms of labor market outcomes. Looking at data of the first lockdown and the subsequent recovery, we shed some light on both dimensions. Furthermore, we are interested in which channel is driving the unemployment result, namely separations and job-findings. Figure 3 shows the separation and job-finding rate over time. It becomes evident that the separation rate quickly normalised after a strong hike, but the job finding rate remained subdued to a considerable extent.

Figure 2: Persons in notifications of short-time work and unemployment over time.



Source: Statistics of the Federal Employment Agency.

Besides the ins and outs, there are further flows forming the unemployment pool. However, we neglect them in this paper though they are hit by the pandemic as well. These flows are flows from unemployment to measures of active labor market policy and vice versa, and flows from and to out-of-the-labor-force. For instance, in the first wave of the pandemic further training and other measures of active labor market policy were suspended, which also caused unemployment to rise.

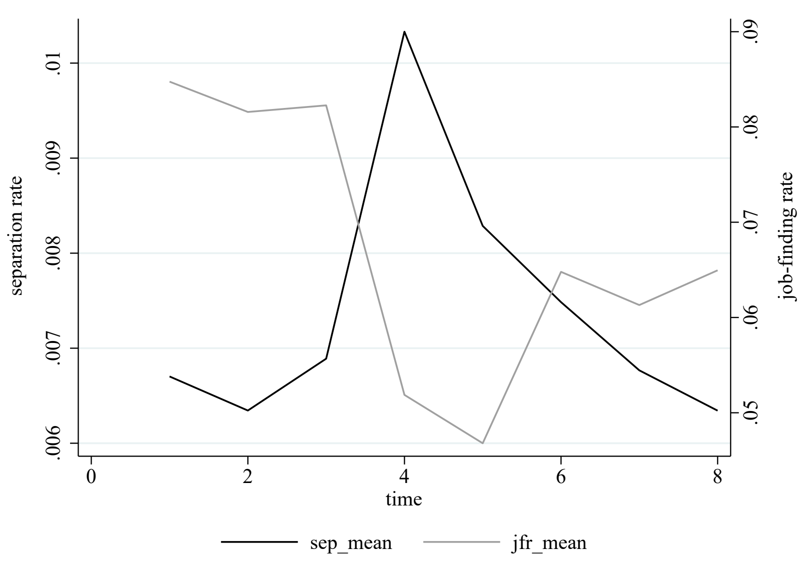
3 Impact Channel: Lockdown length

In this section we want to understand how the length of a lockdown contributes to the rise in the unemployment stock by taking a closer look at the job finding and the separation channel. We use administrative data combined with an innovative data set (see Bauer and Weber, 2020), that keeps track of the course of the measures across regions and time[1].

As dependent variables we use the flows between employment and unemployment for 156 Employment Agency districts. We consider the change in the seasonally adjusted separation

[1] This novel data set includes not just curfews and economic closure, but school closure. The data set is updated regularly and publicly available. See http://doku.iab.de/arbeitsmarktdaten/data_corona_measures.xlsx

Figure 3: Separation rate (left axis) and job-finding rate (right axis) across time.



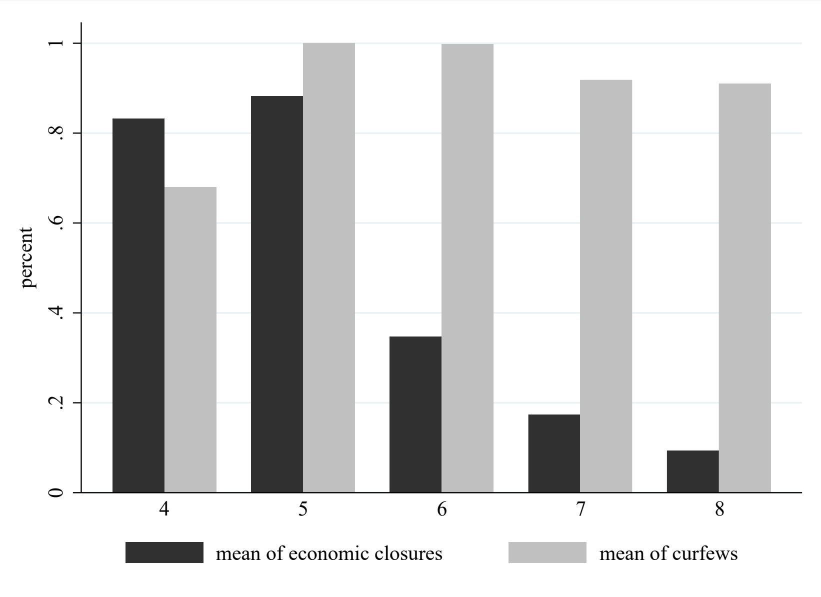
Source: Statistics of the Federal Employment Agency. Own calculations.

and job finding rate from February to August 2020. The former is computed by taking the inflows from employment to unemployment divided by the stock of employment, the latter is determined by taking the outflows from unemployment to employment divided by the stock of unemployment. The flows and stocks are administrative data of the Federal Employment Agency and are counted in between to cutoff dates, where the cutoff date lies in the middle of a month. For instance, for the month of April, the data is measured between the 13th of March and the 14th of April. This is especially important, as the first official governmental reaction regarding Covid-19 was decided on the 12th of March and was implemented on the 13th of March in the federal states. Hence we are confident that our data tracks the evolution of the labor market aggregates, especially between March and April, very detailed.

As explanatory variables we use the days of economic closures and days of curfews. These were determined via comprehensive research and compiled in a dataset. We calculate the days of closure and curfews for a particular month by using the exact same cutoff date as in the administrative data. For the data in April, that means the number of days reflect how early the measures came into force regionally (because all measures persisted at least until mid April). Over time it displays how log the lockdown in one agency district persisted in comparison to another. The measures in the Employment Agency districts vary mainly because districts belong to different federal states, but in some districts certain special measures exist. The data on closures were researched for the sectors of retail, accommodation, restaurants, bars/clubs, cinemas, trade fairs/large-scale events, smaller events, other education, art/entertainment/recreation and hairdressers/cosmetics, and combined into one closure variable per district by averaging.

Figures 4 and 5 show the two variables over time and aggregated at the level of the federal states. Though one might expect that there are more cautious states or districts which might directly transforms into more economic closure days and curfews at the same time, Figure 5 shows that this appears not to be the case in Germany. A higher number of curfews is not automatically connected with a high number of economic closures. Furthermore, because the infection rate in the economy declined over time, the number of days of the measures is decreasing over time as well. The figures depict the relative numbers of days. In absolute terms, considering the 156 districts, there are on average 15 closing days (standard deviation of 10) across the period under consideration. The average for the days of curfews is 27 days (standard deviation of 6).

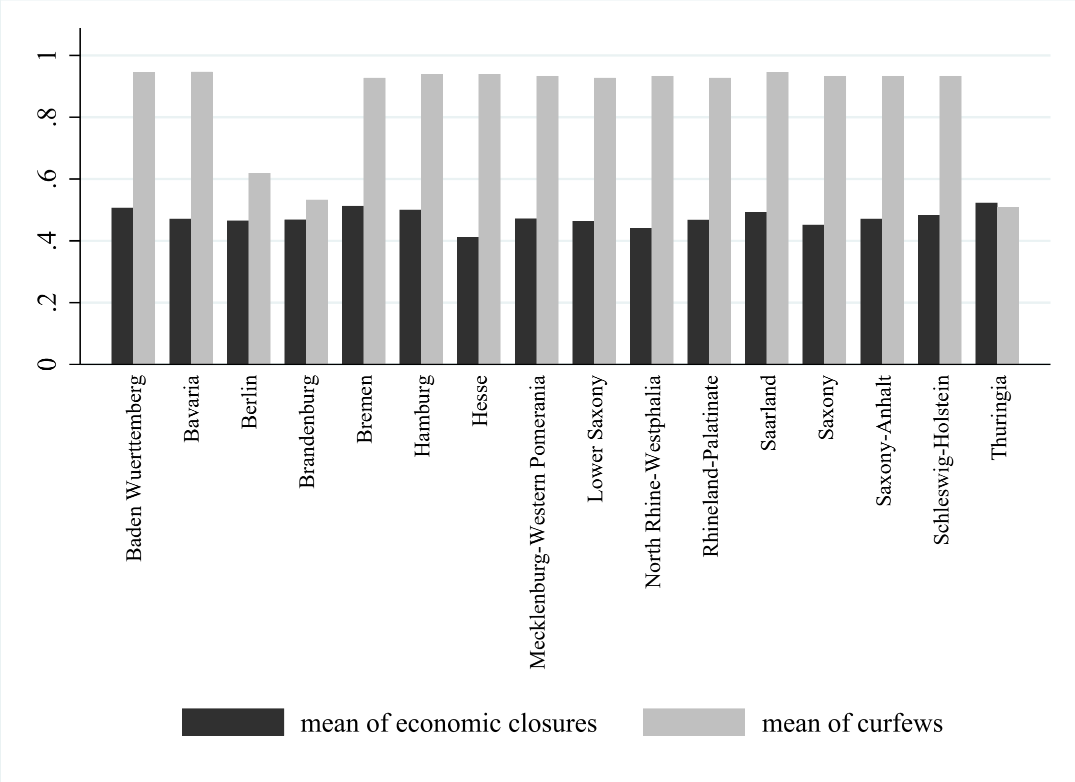
Figure 4: Average number of days of economic closures and curfews over time



Note: Figure 4 shows the days of economic closure and curfews relative to the total days of the certain month for each month beginning in April.
Source: own calculations.

We run fixed effects regression, weighted by the stock of employment to account for the district size. This implies that the industry composition, the labor market status before the crisis, and the regional differences are controlled for. Further we include the regional COVID-19 infection rate at the cutoff date of the respective month. Several states never terminated the curfew but instead changed the mode of the curfew, for instance, they allowed people from one household to meet with another households. To control for potential bias in the curfew variable, we add a variable that collects the number of days per month, in which people from two different households can meet. Furthermore we include autoregressive parameters up to lag 2. This controls for any persistence of the outcome variables. The regression equation reads as follows:

Figure 5: Average number of days of economic closures and curfews across federal states



Note: Figure 5 shows the days of economic closure and curfews relative to the total days of the certain month for each federal state.
Source: own calculations.

$$\text{flow rate}_{it} = \beta_{0i} + \beta_1 \text{curfew}_{it} + \beta_2 \text{economic closure}_{it} + \text{controls}_{it} + e_{it} \tag{3.1}$$

The regression results in Table 1 shows, that the economic closures have an effect of +0.0152 on the separation rate, which means that one more closing day raises the regional separation rate by 1.52 percent. On top, an additional day of curfew leads to an increase in the separation rate by 0.13 percent. On the job-finding rate, the variable of economic closures has an effect of -0.0106, i.e. another closing day leads to a 1.06 percent lower job-finding rate. Curfews decrease the job-finding rate by 0.61 percent. Both channels operating via separations and new hires are relevant. While curfews appear to have a reaction of similar size, economic closures appear to have a stronger effect on the separation margin.

As the days of closure and the curfews are hump-shaped over time, we also added nonlinearities, that drive our results. This is our preferred regression. We find that adding squared terms of the variables on economic closures and curfews initially strengthens the effect: for the separation rate we find an increase of 2.7 percent, and for the job-finding rate a decrease

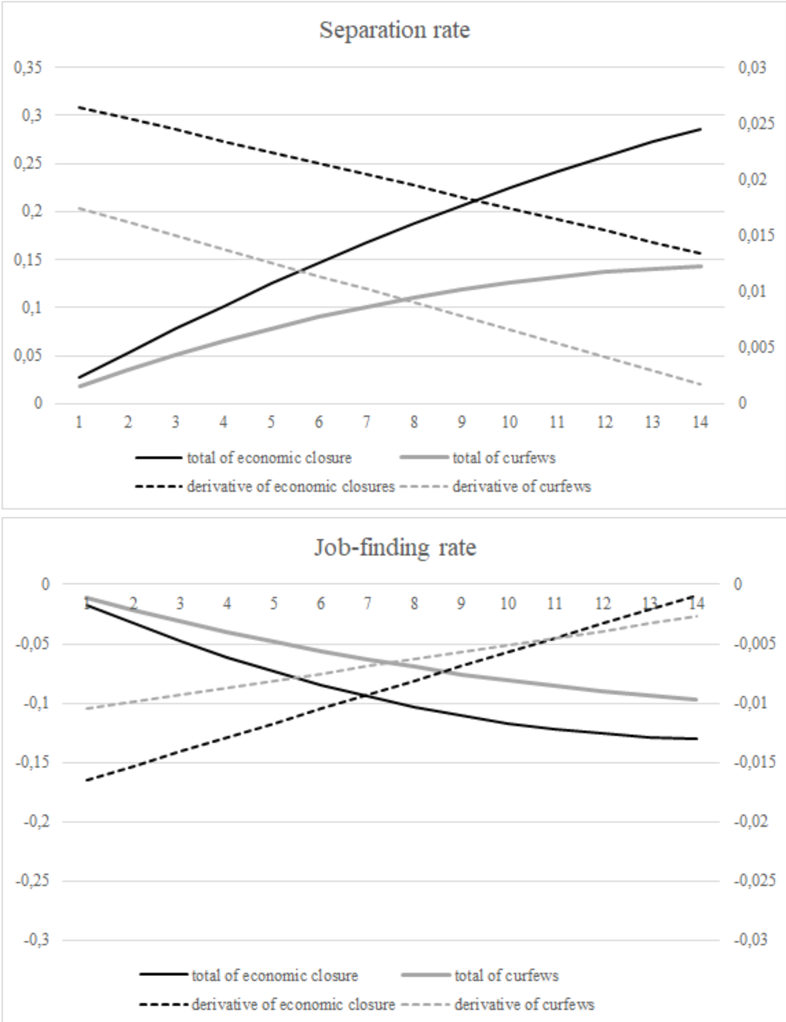
Table 1: Regression of labour market flows on closing days - Robustness Check

Dependent variable	log(Separation rate)		log(Job-finding rate)	
Economic closures	0.0152	0.02743	-0.0106	-0.0177
	(15.64)	(8.42)	(-10.41)	(-4.10)
Economic closures (squared)		-0.0005		0.0006
		(-3.77)		(3.20)
Curfew	0.0013	0.0186	-0.0061	-0.0111
	(2.23)	(8.49)	(-5.18)	(-3.19)
Curfew (squared)		-0.0006		0.0003
		(-7.90)		(2.38)

Note: T-values in parenthesis. Robust (Huber/White) standard errors. Regression weighted by stock of employment.
Source: Statistics of the Federal Employment Agency, own calculations.

of 1.8 percent. Furthermore, the effects are not constant over time. In Figure 6 we show how the effects evolve over a certain time horizon (upper panel), and that the marginal effect of another day of closure (which is given by the first derivative) is decreasing over time for separations, and increasing over time for job-findings (see lower panel).

Figure 6: Total and marginal effects of economic closures (solid lines) and curfews (dotted line) on separation rate (upper panel) and job-finding rate (lower panel)



Note: Own calculations.

4 Impact Channel: Lockdown strength

In this section we make use of job findings and separations (in levels) across industry sectors (NACE Rev. 2, 2-digit) for the 16 federal states in Germany. We deviate here from the regional classification used in section 4 because of data availability. Furthermore, we cannot compute a job finding rate, as unemployment by industry sector is nonexistent.

We use a difference-in-difference approach, distinguishing industries that are treated by the economic closures from the other industries. We use a special application of this approach by replacing the binary treatment by the ”bite”. We borrow this procedure from the literature that is concerned with the measurement of the effects of a nationwide minimum wage on employment (see, for instance, Card(1992) or a recent application from Caliendo et al. (2018)). We use a variable that is bounded between 0 and 1 and indicates to which degree an industry sector was closed in the lockdown between mid March and April. For sectors that were closed by decree and are an enclosed sector in the NACE Rev. 2 classification, we assume a closure of 100 percent. Those sector are, for instance, the travel sector and services in recreation and sports. Also the automobile industry[2] closed fully.

For sectors that were not fully closed by decree but faced some exemptions or in cases where sectors were closed that are smaller than the category in the NACE Rev. 2 classifications we assume a degree of closure by relying on several statistics, such as data on the sales volume, sector size within the 2-digit category, productive share and demand projections. This provides the following assumptions: For ”Wholesale and retail trade and repair of motor vehicles and motorcycles” we set the closure to 50 percent, approximating the share of trade while garages were still operating. Accommodation and Food and beverage service activities is one industry in our classification, and, because restaurants were allowed to offer take-away service, we assume a closure of this industry of 80 percent, which is based on the loss in sales volume according to the Federal Statistical Office. For wholesale and retail we assumed 40.5 percent, as groceries, pharmacies, drug stores and gas stations, which already make up 50 percent in terms of the productive share, were still running during lockdown and faced an increase in demand. For land transport and transport via pipelines we set the rate to 32.8 percent, which stands for the majority of passenger services which also faced a decrease in demand of about 20 percent. Libraries, archives, museums and other cultural activities, Creative arts and entertainment activities and Gambling and betting activities in sum are closed to 70 percent, because most of the industries were closed by decree, except gambling. Other personal service activities is assumed to be closed about 58 percent which corresponds to the share of beauty treatments and hair dressers within the industry. Below 20 percent of clo-

[2] While the automobile industry was not closed by decree, because of its factural shutdown we take it as treated (just as parts of transport.)

sure was given to the industries of Education (standing for education beyond the schooling system), Security and investigation, Services to buildings and landscape, office support and other business support activities (which approximates the share of exhibition stand construction which is situated within that sector), Motion picture, video and television programme production, sound recording and music publishing activities (corresponding to the production share of cinemas).

We use random effect models and control for a comprehensive set of variables which stem from the Establishment History Panel (BHP)(see Ganzer et al. (2020) for a full description of the data set). The BHP is a cross sectional dataset that contains all the establishments in Germany which are covered by the IAB Employment History (BeH) [3] and have at least one employee liable to social security. We use the BHP to add information on the average share of certain worker groups in the establishments operating in the industries in the regions, information about the average wage structure and the age of the establishments. Furthermore, we control for the infection rate at the cutoff date of the respective month.

Our estimation equation reads as follows:

$$log(flow)_{ijt} = \beta_{0ij} + \gamma_1 month_t + \gamma_2 close_i + \gamma_3 month_t \times close_i + \beta X_{ij} + u_{ijt}, \tag{4.1}$$

where $log(flow)_{ijt}$ holds the logged separations or hirings in region i, industry j and time t (March to August 2020). $month$ is a time dummy that takes on the value of 1 in the respective month. As first closure measures came into force on March 13th, and the inflows in April are measured between 13th of March and 14th of April, the April dummy is the first point in time after lockdown. The reference date is March. The variable $close$ is bounded between 0 and 1, showing the degree of closure of an industry during lockdown and is time-invariant. The logic is the following: On the one hand the degree of economic closures during the lockdown has a direct effect on the flows in April, but it might also be the case that the effects spills over to the proceeding months. We check this by assessing a treatment effect for each month from April to August. This treatment effects are given by the interaction term of $month$ and $close$ with coefficient γ_3. This interaction measures the strength of the treatment effect because of the closure measures due to COVID-19. X holds the control variables with coefficient vector β, and u_{ijt} is an industry-region-time specific error term.

Table 2 shows the effects of interest. A change in the degree of closure (from 0 to 1, i.e. 100 percent) increases separations across industry and region by initially 46 percent and decreases job-findings by 46 percent. This effect vanishes out over the following months. While for sepa-

[3] For more information follow this link.

rations the effect persists until July, for the job-findings the effects already vanish in June (statistically insignificant) [4]. A back-of-the-envelope calculation in which we multiply the mean degree of economic closure in the total economy with the (significant) coefficient of the interaction terms, and sum over time, we end up with an average total effect on separations of roughly 11 percent and on job findings of -12 percent. This implies that while the job finding rate remained subdued also after the end of the lockdown (Figure 3), this was a broader effect of the general crisis and no causal effect confined to the lockdown sectors.

Table 2: Regression of separations and hirings on degree of closure

		log(separations)	log(hirings)
treatment		0.5010	0.5668
		(2.86)	(2.98)
time			
	April	0.2012	−0.3245
		(13.00)	(−18.68)
	May	0.1412	−0.3050
		(7.55)	(−14.15)
	June	0.0465	−0.0002
		(2.42)	(−0.01)
	July	−0.0211	−0.0751
		(−1.07)	(−3.23)
	August	−0.0492	0.0086
		(−2.33)	(0.34)
time × treatment			
	April	0.4643	−0.4620
		(9.26)	(−8.62)
	May	0.2030	−0.5416
		(4.20)	(−10.72)
	June	0.1179	0.0512
		(2.55)	(0.80)
	July	0.1168	0.0892
		(2.39)	(1.89)
	August	0.0439	−0.0036
		(1.06)	(−0.07)

Note: T-values in parentheses.
Source: Statistics of the Federal Employment History; Establishment History Panel 2018, own calculations.

[4] As the closure variable is bounded between 0 and 1, expansion bias might exist (see Rigobon and Stoker, 2007)

5 Short-time work

In Germany - just as in many other countries - the labour market was shielded from the crisis effects by job retention schemes at large scale. Hence, in this section, we apply our regression framework to notifications for short-time work (see figure 2). Each firm has to apply for short-time work, and indicate how many workers will be covered by this job retention scheme. If firms are eligible, they will send their employees in short-time work, which will receive compensation from the Federal Employment Agency. We devide the number of persons in short-time work by the number of employees in the respective month and in the respective Employment Agency district. This leaves us with a short-time work rate, which we then log. Running regressions in the same spirit as in section 4 provides the following results.

Table 3: Regression of persons in short-time work on closing days and curfews

	log(rate of short-time workers)
Economic closures	0.0556
	(21.13)
Curfews	0.0051
	(1.75)

Note: T-values in parentheses. The time series starts in January. Additional controls: Dummy indicating when it was allowed to meet persons of more than one household, the rate of infection at the cutoff date.
Source: Statistics of the Federal Employment History; Establishment History Panel 2018, own calculations. ©IAB

Table 3 shows that economic closures have stronger effects on the share of short-time work than curfews. While economic closure increase the rate of short-time work by roughly 6 percent, curfews increase it by 0.5 percent.

Because the number of workers in short-time work reacted earlier as unemployment, we start with the treatment period earlier than in the regressions above. Table 8 shows that the initial impact of the lockdown was high, but that the effect gets smaller over time. For non-treated industries (sectors not directly affected by closures), the effect starts at an increase of short-time work of 243 percent in March and for treated sectors (sectors with a certain degree of closure) the short-time work increased by even 400 percent. That implies, that the industry sectors that were hit hardest in terms of closure, used a lot more short-time work, namely 400 percent more than not directly affected industries.

Table 4: Regression of persons in short-time work on degree of closure

		log(persons in short-time work)
treatment		-2.6537
		(-8.03)
time		
	March	2.4302
		(26.85)
	April	3.2531
		(28.31)
	May	3.1979
		$(24.80))$
	June	2.9208
		(21.66)
	July	2.5772
		(18.63)
time × treatment		
	March	4.0405
		(11.17)
	April	3.8110
		(11.10)
	May	3.6234
		(10.67)
	June	3.5157
		(10.44)
	July	3.4342
		(9.95)

Note: T-values in parentheses.
Source: Statistics of the Federal Employment History; Establishment History Panel 2018, own calculations.

6 Robustness

6.1 Robustness on length

We further checked to which extent the lockdown shows prolongated effects by controlling for lags. Table 6shows that this procedure gives results that lie between the basic version and the non-linear version but has a lot of insignificant effects.

Table 5: Regression of labour market flows on closing days - Robustness Check

Dependent variable	log(Separation rate)	log(Job-finding rate)
Economic closures	0.0109	-0.0127
	(7.58)	(-6.48)
Economic closures (lagged)	0.0113	-0.0024
	(10.48)	(-1.83)
Curfew	0.0019	0.0000
	(1.70)	(0.00)
Curfew (lagged)	0.0041	-0.0053
	(0.28)	(-2.88)

Note: T-values in parenthesis. Robust (Huber/White) standard errors. Regression weighted by stock of employment.
Source: Statistics of the Federal Employment Agency, own calculations.

6.2 Robustness on strength

In the main regression we used an estimate of degree of closure. In this robustness check we consider two alternatives: First, we replace the degree of closure by a dummy variable. This allows to estimate a classical diff-in-diff. Second, we instead use the share of the gross value added affected by the closures in the industries that were not directly treated. The logic behind is the following: While some industries are closed per decree, others were hit by these measures through their linkages to the closed industries. To account for the full extent, we generate the change in the gross value added of every industry caused by the closures via their linkages in an input-output table. A full list of the degrees of closure and the loss in value added including input-output linkages is given in the appendix.

Table 6: Regression of separations and hirings on degree of closure using input-output linkage

	Dummy variable		loss in gross value added	
	log(separations)	log(hirings)	log(separations)	log(hirings)
treatment	0.8350	0.8606	0.5848	0.6121
	(7.44)	(7.66)	(3.51)	(3.43)
time				
April	0.1985	-0.3294	0.1786	-0.3005
	(12.48)	(-18.38)	(11.10)	(-15.33)
May	0.1406	-0.3190	0.1329	-0.2735
	(7.30)	(-14.43)	(7.02)	(-11.88)
June	0.0494	-0.0008	0.0443	0.0092
	(2.50)	(-0.03)	(2.22)	(0.38)
July	-0.0090	-0.0813	-0.0269	-0.0739
	(-0.45)	(-3.43)	(-1.30)	(-2.94)
August	-0.0475	0.0013	-0.0491	0.01273
	(-2.20)	(0.05)	(-2.25)	(0.48)
time $\times$ treatment				
April	0.2758	-0.2366	0.4447	-0.4487
	(10.04)	(-8.08)	(12.37)	(-10.11)
May	0.1148	-0.2429	0.1859	-0.5421
	(4.68)	(-7.45)	(5.17)	(-12.21)
June	0.0506	0.0325	0.0941	-0.0127
	(2.20)	(1.10)	(2.62)	(-0.28)
July	0.0114	0.0768	0.1120	0.0564
	(0.43)	(3.33)	(3.11)	(1.27)
August	0.01257	0.0295	0.0302	-0.0238
	(0.55)	(1.14)	(0.84)	(-0.54)

Note: T-values in parentheses.
Source: Statistics of the Federal Employment History; Establishment History Panel 2018, own calculations.

6.2.1 Timing of events

In the main regression we decided to use March as the reference month. This procedure allows us to appropriately determine the effect of the closure measure by reducing the omitted variable bias via controlling for the regional infection rate, which is not filled before March. However, in this robustness check we performed a regression where we set the pre-crisis period to January instead of March (i.e. assume an infection rate of zero before March). This leaves us with results that are very similar in size and significance. Most importantly, it shows that the treatment effects in February and March are negligible and insignificant. Accordingly, March appears to be a proper reference month.[5] See Table 8 in the Appendix for the results.

6.2.2 Back-of-the-envelope calculations

In order to assess the explanatory power of the regression results in Table 6, we run the following computations: First we assess how many more separations and less job-findings exist by applying the coefficients of the treatment effects between April and August to the mean level of separations and job findings between January and March and multiply this expression which the loss in output. Then we sum these additional separations and job findings over time which gives us a cumulative treatment effect in both variables. Second we calculate the cumulative increase in separations and job findings in our data accordingly and compare these numbers. We can explain about 31 percent of the increase in separations, and about 33 percent of the reduction in job findings. Overall, this stands for 80 thousand more people in unemployment.

Note that this does not equal the total number of additional separations (or lost hirings) in the affected sectors: The treatment effect measures only the part that exceeds the effect all sectors were subject to. I.e., a substantial part of the labour market reaction was not directly due to domestic containment measures, but due to other general crisis effects. Candidates are increased uncertainty, worsened expectations, supply chain problems and reductions in export demand.

[5] Note that we also visually inspected the common trend assumption in the binary case, which shows no abnormality.

7 Conclusion

We find that in Germany, especially the separations increased through the containment measures. While the length of the lockdown was identified in an innovative data set that tracks the number of days of economic closure and curfew, the strength of the lockdown was given by the estimated degree of closure mainly based on national statistics on sales and industry share of industries hit.

For the length of the lockdown we find that an additional day of closure lead to an increase in the separation rate of 2.7 percent and a decrease in the job-finding rate of 1.8 percent. For the strength of the lockdown the results show that a higher degree of closure, increase separations and lower job findings to a similar extent. In both dimensions, we find that the effects are non-linear over time.

For the effects of the lockdown length, the non-linearities shed light on the question, whether an additional day of lockdown is more painful or not. We find that further days are less important once the lockdown already started. A possible explanation might be that economic agents learn to deal with the situation.

The nonlinearities in the strength regression, show that the additional effects of the spring lockdown quickly taper off. While Figure 3 shows that the separation rate indeed normalised, this does not hold for the job finding rate. However, the fact that job findings remained subdued also after the end of the lockdown has been a broader effect of the general crisis and no causal effect confined to the lockdown sectors.

For short-time work, we find a significant impact for the length of economic closures and curfew. The effect of economic closures on short-time work is ten times stronger than the effect of the curfews. For the strength of the measures, we also find clear significant effects. Industries that are particularly hit by the crisis use short-time work considerably oftener. Again these effects are non-linear over time.

In a nutshell, economic closures impact unemployment flows and the number of short-time workers more strongly than curfews. Both, separations and job findings are affected. The lasting hiring weakness after the lockdown is not specific to lockdown sectors. In a back-of-the-envelope calculation, we find that 31 percent of the considerably increased inflows from employment into unemployment, and 33 percent of the reduced outflows from unemployment to employment in the first wave were due to the treatment effect of the lockdown measures. This increased unemployment in the short run by 80,000 persons.

When assessing these results, two points should be kept in mind: First, the available data measure effects up to August. Secondly, we consider immediate effects in the first wave. These are probably not applicable to the second wave as there are learning effects for the firms and a more positive perspective due to progressive vaccinations. Without the measures, however, an uncontrolled spread of the virus could possibly have caused much greater damage in the medium run.

Notwithstanding, our results show which opportunity costs of the containment measures and their length and strength have to be taken into account by policy makers.

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Appendix

8 Input-Output Linkage

Table 7: Inflows to unemployment from employment subject to social security contributions

Code	”Classification of Products by Activity”	loss of value added	degree of closure
01	Crop and animal production, hunting and related service activities	-0,0064	0,0000
02	Forestry and logging	-0,0030	0,0000
03	Fishing and aquaculture	-0,1151	0,0000
05	Mining of coal and lignite	0,0000	0,0000
06	Extraction of crude petroleum and natural gas	-0,0070	0,0000
07-09	Mining and quarrying and mining support service	-0,0005	0,0000
10-12	Manufacture of food products, beverages, tobacco	-0,0425	0,0000
13-15	Manufacture of textiles and wearing apparel	-0,0227	0,0000
16	Manufacture of leather, wood and cork	-0,0357	0,0000
17	Manufacture of paper and paper products	-0,0303	0,0000
18	Printing and reproduction of recorded media	-0,0995	0,0000
19	Manufacture of coke and refined petroleum products	-0,0507	0,0000
20	Manufacture of chemicals and chemical products	-0,0109	0,0000
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations	0,0000	0,0000
22	Manufacture of rubber and plastic products	-0,1371	0,0000
23	Manufacture of other non-metallic mineral products -0,0388	0,0000	
24	Manufacture of basic metals	-0,1872	0,0000
25	Manufacture of fabricated metal products, except machinery and equipment	-0,1089	0,0000
26	Manufacture of computer, electronic and optical products	-0,0067	0,0000
27	Manufacture of electrical equipment	-0,0353	0,0000
28	Manufacture of machinery and equipment n.e.c.	-0,0171	0,0000
29	Manufacture of motor vehicles, trailers and semi-trailers	-1,0000	1,0000
30	Manufacture of other transport equipment	-0,0058	0,0000
31-32	Manufacture of furniture and Other manufacturing	-0,0008	0,0000
33	Repair and installation of machinery and equipment	-0,1089	0,0000
35	Electricity, gas, steam and air conditioning supply	-0,0609	0,0000
36	Water collection, treatment and supply	-0,0698	0,0000
37-39	Sewerage, Waste collection, disposal and remediation activities	-0,0524	0,0000
41	Construction of buildings	-0,0021	0,0000
42	Civil engineering	-0,0118	0,0000
43	Specialised construction activities	-0,0314	0,0000
45	Wholesale and retail trade and repair of motor vehicles and motorcycles	-0,7545	0,5000
46	Wholesale trade, except of motor vehicles and motorcycles	-0,4581	0,4050

Code	”Classification of Products by Activity”	loss of value added	degree of closure
47	Retail trade, except of motor vehicles and motorcycles	-0,4453	0,4050
49	Land transport and transport via pipelines	-0,5316	0,3280
50	Water transport	-0,0231	0,0000
51	Air transport	-0,9222	0,7500
52	Warehousing and support activities for transportation	-0,6988	0,5000
53	Postal and courier activities	-0,2115	0,0000
55-56	Accommodation and Food and beverage service activities	-0,8231	0,8000
58	Publishing activities	-0,0503	0,0000
59-60	Motion picture, video and television programme production and Programming and broadcasting activities	-0,0249	1,0000
61	Telecommunications	-0,0643	0,0000
62-63	Computer programming, consultancy and related activities and Information service activities	-0,0528	0,0000
64	Financial service activities, except insurance and pension funding	-0,0493	0,0000
65	Insurance, reinsurance and pension funding, except compulsory social security	-0,0471	0,0000
66	Activities auxiliary to financial services and insurance activities	0,0000	0,0000
68	Real estate activities	-0,0580	0,0000
69-70	Legal and accounting activities and Activities of head offices; management consultancy activities	-0,0711	0,0000
71	Architectural and engineering activities; technical testing and analysis	-0,0457	0,0000
72	Scientific research and development	0,0000	0,0000
73	Advertising and market research	-0,1372	0,0000
74-75	Other professional, scientific and technical activities and Veterinary activities	-0,0790	0,0000
77	Rental and leasing activities	-0,0913	0,0000
78	Employment activities	-0,1606	0,0000
79	Travel agency, tour operator and other reservation service and related activities	-1,0000	1,0000
80-82	Security and investigation, Services to buildings and landscape, office support and other business support activities	-0, 7670	0,1600
84	Public administration and defence; compulsory social security	-0,0114	0,0000
85	Education	-0,1399	0,1300
86	Human health activities	-0,0012	0,0000
87-88	Residential care activities and Social work activities without accommodation	0,0000	0,0000
90-92	Entertainment activities, Libraries, archives, museums and Gambling	-0,7180	0,7000
93	Sports activities and amusement and recreation activities	-1,0000	1,0000
94	Activities of membership organisations	-0,0335	0,0000
95	Repair of computers and personal and household goods	-0,0861	0,0000
96	Other personal service activities	-0,5967	0,5800
97-98	Activities of households, goods- and services-producing activities of private households for own use	0,0000	0,0000

Source: Federal Statistical Office. Own calculations.

9 Timing of events

Table 8: Regression of separations and hirings on degree of closure - reference month January

		log(separations)	log(hirings)
treatment		0.5138	0.5346
		(2.91)	(2.85)
time			
	February	−0.0271	−0.0368
		(−3.01)	(−3.34)
	March	0.0515	−0.0299
		(5.61)	(−2.68)
	April	0.2604	−0.3698
		(23.59)	(−24.89)
	May	0.2035	−0.3563
		(17.93)	(−25.94)
	June	0.1098	−0.0536
		(9.62)	(−3.82)
	July	0.0429	−0.1298
		(3.88)	(−10.50)
	August	0.0160	−0.0484
		(1.45)	(−3.63)
time × treatment			
	February	0.0050	0.0118
		(0.19)	(0.39)
	March	−0.0148	0.02286
		(−0.46)	(0.71)
	April	0.4495	−0.4395
		(9.74)	(−7.81)
	May	0.1882	−0.5193
		(4.38)	(−9.67)
	June	0.1033	0.0734
		(2.21)	(1.06)
	July	0.1022	0.114
		(2.16)	(2.10)
	August	0.0293	0.0187
		(0.69)	(0.32)

Note: T-values in parentheses.
Source: Statistics of the Federal Employment History; Establishment History Panel 2018, own calculations. ©IAB

Imprint

IAB-Discussion Paper 10|2021

Publication Date
28 July 2021

Publisher
Institute for Employment Research
of the Federal Employment Agency
Regensburger Straße 104
90478 Nürnberg
Germany

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