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DISCUSSION PAPER

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Hospital Capacity Reporting in Germany During COVID-19

Hospital capacity reporting in Germany during Covid-19 ♡

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Abstract

During the COVID-19 pandemic, hospitals faced a unique predicament. Hospital care was urgently needed and society took efforts to prevent overwhelming hospitals. However, hospitals in case-based reimbursement schemes faced financial problems because of cancelled elective care visits and government regulations to keep capacity free for Covid-19 patients. Therefore, emergency financing measures were implemented in many countries. We analyze how hospitals in Germany responded to a scheme that provided financial support if the intensive care unit (ICU) occupancy rate in a county exceeded 75%. The scheme distributed over seven billion euros to hospitals and was notable because financial support depended on a measure (ICU occupancy rate) that hospitals could directly influence. To analyze hospitals' reactions to this scheme, we employ event study analyses comparing ICU capacity before and after regions became eligible. We find no evidence of strategic reporting at an economically meaningful and hence empirically detectable scale.

JEL codes: I11, I18, H27
Keywords: Hospitals, Misreporting, Financial Support Programs, Covid

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1 Introduction

In numerous countries, hospitals are funded by prospective payment schemes whereby hospitals receive a fixed amount of money for each patient. The reimbursement rate is prospectively determined by patient characteristics such as diagnosis in diagnosis-related groups (DRGs) (Busse et al., 2013; Schreyögg et al., 2006). During the Coronavirus pandemic, these prospective payment schemes put hospitals under financial pressure for two reasons. First, patients in fear of infection postponed elective care. Second, hospitals were asked to maintain empty beds in anticipation of increased care demand for Covid-19 patients, in particular in intensive care units (ICUs). Without any intervention, hospitals would have seen an immediate decrease in cash flow and revenue. To mitigate these financial struggles, various governments have implemented compensation schemes. In this paper, we analyze how hospitals in Germany responded to the compensation scheme implemented in November 2020, which provided additional funding for hospitals in regions with high infection rates when ICU occupancy rates were high.

Hospitalization risk after contracting Sars-Cov-2, the virus responsible for Covid-19, is highly correlated with age and comorbidities (Sanyaolu et al., 2020; Vahey et al., 2021) but is generally low (five percent of all individuals who tested positive for the virus needed hospital care) across different virus variants (Nyberg et al., 2021; Salje et al., 2020; Twohig et al., 2022). However, the large number of infected individuals and the resulting high number of patients in need of specialized care ultimately did put hospitals under stress. In particular, in the early days of the pandemic, there were multiple examples of regional hospital systems struggling to cope with the number of patients needing ventilation and other forms of intensive care, for example in Wuhan (China) (Time, 2020; Woo & Deng, 2020), Bergamo (Italy) (Orlandi, 2020) and Brazil (Phillips, 2020). Following these early experiences, policymakers in many countries implemented schemes to increase ICU capacity and to allow hospital beds to be reserved in anticipation of a surge in patients (Giraud et al., 2021).

Simultaneously to the increase in demand for ICU care, hospitals experienced a drop in elective care patients, for example in Italy (Spadea et al., 2021), Scotland (Mulholland et al., 2020) or Germany (Augurzky et al., 2022a). This led to a significant drop in revenue for hospitals. Many countries implemented schemes to compensate hospitals for their lost revenue and measures to support the health care system in general. For example, the UK replaced a DRG-based system with global budgets; Germany, France, Belgium, Finland and the Netherlands compensated Covid-19 related loss of revenue directly or provided extra budgets (European Observatory on Health Systems and Policies, 2021;

Giraud et al., 2021; Quentin et al., 2020).

In summary, two different forms of financial support for hospitals were implemented during the pandemic: Schemes targeted directly at ICU capacity and general support for healthcare systems. From an economic perspective, the choice between these two different strategies is a trade-off between two approaches. On the one hand, using financial resources to tackle the acute problem of the pandemic with targeted measures could potentially is cheaper but could miss important aspects. On the other hand, broader emergency financing would benefit every institution in need at the danger of substituting inefficient care structures.[1]

One threat in targeted emergency financing schemes is that potential beneficiaries can strategically adapt the parameters that influence eligibility. In this paper, we study the example of the emergency hospital finance scheme that was in place from November 2020 until June 2021 in Germany. Here, hospitals received extra money for empty beds when the regional Sars-Cov-2 incidence rate crossed a certain threshold and when free ICU capacity in that region was below 25% (we describe the scheme in detail in Section 2). As ICU occupancy rate is at least to some degree a choice variable for hospitals, several media reports (Bodderas, 2021; Grill, 2021; Schrappe et al., 2021) and also the Federal Audit Office (Bundesrechnungshof, 2021) voiced concerns that hospitals strategically underreported their capacity to be eligible for extra reimbursement. Such strategic reporting does not only absorb financial resources but also hinders efficient allocation of ICU patients when information on actual capacity is unavailable. While hospitals reactions to reimbursement schemes in normal times are well explored, we contribute to the literature on emergency funding schemes and hospital behavior in stress situations.

Strategic reporting by hospitals in order to increase revenue is nothing unfamiliar to the health economics literature. There is ample evidence that patient characteristics are upcoded to increase DRG reimbursement (Barros & Braun, 2017; Dafny, 2005; Jürges & Köberlein, 2015), patients are reclassified to reach reimbursement relevant quality thresholds (Gravelle et al., 2010), and that other forms of revenue maximization without patient benefit occur (Cooper et al., 2020). It remains an empirical question whether – and if so – how and to what extent hospitals strategically reported their ICU capacities under the German scheme. In the next Section 2, we describe the scheme in detail. We then outline how we investigate whether strategic reporting took place under this scheme and present our empirical results in Section 4). After that, we conclude with some recommendations for future design of such schemes.

[1] This is a trade-off faced for all relief measures during the pandemic. Examples are also cash transfers for individuals and businesses.

2 Hospital financing during the pandemic in Germany

The first Sars-Cov-2 infection in Germany was detected on the January 27th, 2020 (Süddeutsche Zeitung, 2020). Sars-Cov-2 infections then spread throughout the country in February and March, probably facilitated by an infection cluster in Ischgl (Austria), a popular destination for ski tourists from Germany (Felbermayr et al., 2021). On March 17th, 2020, there were over 7000 detected infections and the German government agency for disease control and prevention (RKI) increased the risk assessment for Sars-Cov-2 in Germany to "high" (Robert Koch Institut, 2020). One week later, the German parliament passed a bill that granted special rights to the government to handle an epidemic of national scale ("Epidemische Lage nationaler Tragweite"). Further regulations for hospitals followed.

2.1 Early hospital support scheme

Hospitals in Germany are financed to a large extent on a case basis through the G-DRG scheme. At the beginning of the pandemic, hospitals faced a sudden reduction in patients seeking elective care and a large increase in spending for protective equipment and hence financial stress. To support the hospital system in this situation, the German government introduced the Covid-19 Hospital Relief Law (Krankenhausfinanzierungsgesetz KHG §21) on March 16th 2020.

Hospitals received €560 in financial aid for every empty hospital bed, calculated as the difference between current patients and the average daily number of patients treated throughout 2019 (GKV-Spitzenverband, 2021). Further, each new ICU bed a hospital created was rewarded with additional financial lump-sum compensation (Giraud et al., 2021).

From July to September 2020, the financial aid for unfilled hospital beds was adjusted to reflect differences in average length of stay and casemix between hospitals. Instead of the uniform payment, daily rates then ranged between €360 and €760 per unoccupied bed compared to 2019.

2.2 ICU capacity based hospital support scheme

Soon after the initial hospital support scheme expired in September 2020, Covid cases increased again, raising fears of excess demand for hospital beds. Therefore, an adjusted hospital support scheme was announced on November 16th, 2020 which took effect two days later and aimed to incentivize hospitals to reserve capacity for Covid patients. This reformed scheme still contained the flat payments from the earlier scheme (between

€360 and €760 per unfilled bed compared to 2019) but payout depended on regional conditions. Hospitals received the financial support only when the county was severely affected by Covid based on two measures: Condition 1) The incidence rate in a county needed to be at least 70.[2] Condition 2) The share of free ICU beds in a county needed to be below 25%.[3] In the six weeks from November 18th, 2020 to the end of 2020, hospitals received 1.26 billion Euros through this scheme (Augurzky et al., 2021) and an additional 5.83 billion Euros in 2021 (Augurzky et al., 2022b). The scheme was in place until June 15th, 2021.

2.3 ICU capacity reporting

Hospitals were required to report the number of readily available ICU beds and the number of occupied ICU beds to a central public registry every day (DIVIIntRegV §1). Number of ICU beds hereby does not mean physical beds but instantly available beds including technical devices and staff, a measure which is difficult to validate for public authorities. This leaves degrees of freedom for the hospital in reporting the number of ICU beds. Thus, there was an opportunity for hospitals to report fewer readily available beds to cross the 25% free ICU capacity threshold – and become eligible for extra funding. While non-reporting is sanctioned by a reduction in the support payments, accuracy of reporting was not audited (DIVIIntRegV §3).

Overall, the German hospital support scheme shifted from an unconditional to a conditional support system, specifically targeting hospitals with larger exposure to the pandemic and more tense situations in hospitals. However, the regulation for hospital support in Germany might have set incentives to strategically report the number of free ICU beds to receive extra financial compensation.

3 Incentives and hypotheses

To evaluate whether strategic reporting is beneficial for hospitals, we consider the different possible scenarios a hospital might find itself in and search for the best behavior. We rely on the following assumption: Even though the detection probability and

[2] Incidence rate in Germany refers to PCR test (polymerase chain reaction test) detected Sars-Cov-2 cases per 100,000 inhabitants within the last seven days.

[3] Additionally, the individual state had to approve eligibility of an individual hospital for help payments. However, states had no incentive not to allow support for hospitals. Between December 17th, 2020 and January 14th, 2021, condition two was removed when the incidence level was at least 200. From January 15th onwards, condition two was removed when incidence was at least 150. Finally, two special regulations were introduced. First, additional hospitals may be eligible for payments when free ICU capacity is below 15%. Second, when there is no hospital in one county, a neighboring county can be awarded further financial aid.

the sanctions of non-accurate reporting were arguably small, there were still organisational costs associated with strategic reporting, e.g. to determine the optimal capacity to report and to monitor reported data of other hospitals. Since the conditions of the financial support scheme are evaluated at the county level - not for individual hospitals - the coordination costs for colluding are higher the more hospitals in a county operate an ICU and are zero for hospitals that are the single provider of ICUs in their county. We assume organisational costs are smaller than extra compensation via the support scheme.

The following cases arise for the hospitals under the support scheme. Case 1: In case the incidence in a county is below 70 (condition 1 for the financial support scheme is not met), the hospital does not receive extra compensation independent of the ICU occupancy. Altering reporting hence causes organisational cost, but provides no benefit. We therefore expect hospitals to report accurately in this case.

Case 2: If, however, the county-level incidence is at least 70 (condition 1 for the financial support scheme is met), incentives differ by the actual ICU capacity. In counties with less then 25% of ICU beds available, there is no need to alter reporting since the hospital already qualifies for the extra compensation. This extra compensation depends on the number of patients treated compared to the previous year - not on the number of reported ICU beds. Again, altering reporting causes organisational cost, but provides no benefit. We therefore expect hospitals to report accurately in this case.

Case 3: For hospitals in counties with more than 25% of ICU beds available, there are three possible options: If all hospital reports accurately no hospital receives extra compensation. However, hospitals could use two strategies so that hospitals in this county become eligible for extra compensation. On the one hand, they could transfer patients from normal care to the ICU, reducing the share of available ICU beds to below 25%. In this case, the hospital receives extra compensation but both the organizational costs as well as the costs for transferring the patients occur. On the other hand, hospitals could report less available ICU beds, also reducing the share of available ICU beds to below 25%. Again, the hospital is eligible for extra compensation with only organisational cost. Not all hospitals in a county need to behave equally, some could strategically report while others free-ride. If all hospitals rely on strategic reporting of other hospitals, only actual capacities are reported and the fist case of no extra compensation applies. In counties with only one ICU provider free-riding is not possible, however, organisational costs are especially small - giving hospitals a larger incentive to reduce the number of reported available ICU beds.

Given these different options in Case 3, we expect that hospitals reduce their number of available ICU beds once the condition of a high incidence level is reached.

4 Empirical analysis

In our empirical analysis we use two strategies to investigate whether reporting of ICU capacities changed after the occupancy-based funding scheme started. First, we use a set of bivariate analyses to show whether the distribution of ICU beds changed around the incidence threshold of 70 and check for heaping in the distribution of free ICU beds at the eligibility threshold of 25%. Second, we use two-way-fixed-effects (TWFE) estimations to analyze how the number of available ICU beds changed after the incidence threshold of 70 was crossed in each county.[4]

4.1 Data description

Our analysis is based on a county-day panel constructed from three different sources. First, we use the reported occupied and available beds in the ICU registry operated by the German Association of Intensive Care Physicians ("DIVI Intensivregister").[5] Hospitals report information on the number of ICU beds and whether they are 1) available, 2) occupied and 3) occupied by Covid patients to the registry. Hospitals are required by law to report their figures to the registry every day (DIVIIntRegV §1). This raw data is then aggregated at the county level. Hence, we observe the number of ICU beds at the same aggregated level that was used to determine eligibility for the financial support scheme. Our second data source is hospital information from the annual German hospital report which contains information on every hospital in the country.[6] This data contains information on the hospital ownership type as well as hospital size in terms of beds and cases. Out of all hospitals in Germany, we only include those with an ICU and then aggregate hospital data combined with ownership information to the county level. As a third data source, we use data on incidence levels for each day. We use data on incidence levels as they were reported on the respective days – without adjustments or corrections – as this is the indicator that determined eligibility for the extra funding.[7]

In our final data set we need to exclude some of the 401 counties due to data re-

[4]An intuitive third option would be to run regression discontinuity design estimations using the incidence as running variable and the threshold of 70 as the threshold (condition 1) that induces changes in reported ICU capacity. We show in Appendix B that this approach is unsuited in our setting.

[5]The data can be accessed here: https://www.intensivregister.de/.

[6]The reports can be found here: https://www.wido.de/publikationen-produkte/buchreihen/krankenhaus-report/.

[7]Historical, uncorrected incidence levels are only available from November 18$^{\text{th}}$, 2020 onwards, for dates preceeding November 18th, we are restricted to official incidence rates corrected for late-reporting.

strictions and continue our analyses with 394 counties.[8] Our unit of observations are county-day observations from November 2020 to April 2021. In Table 1, we present descriptive statistics of our data. We observe the 394 counties for 152 days resulting in 59,888 county-day observations. On average, counties had an ICU capacity of 65 beds of which on average 21% were free. There were on average 2.72 hospitals with ICUs in a county, and in 9% of the counties, all ICU beds are operated in private hospitals.

Table 1: Descriptive statistics

	N	Mean / Share	SD	Min	Max
Day-County Observations	59888				
Reported incidence		119.73	76.51	0	885.41
Share free ICU beds		21%	0.13%	0%	100%
ICU capacity		65.12	80.03	3	741
Counties	394				
ICU hospitals per county		2.72	2.45	1	24
Share counties with all ICUs in private hospitals		9%			
Counties with 1 ICU hospital	133				
Reported incidence		125.15	50.81	28.47	296.83
ICU capacity		25.24	21.52	4.97	134.22
Share counties with all ICUs in private hospitals		18%			

Notes: Descriptive statistics for day-county observations and at the county level from November 18th, 2020 - April 8th, 2021. ICU capacity refers to the number of total ICU beds reported by all hospitals in a county. Reported Incidence is the number of PCR-positive Sars-Cov-2 cases per 100,000 inhabitants in the last seven days reported on the day without later corrections.

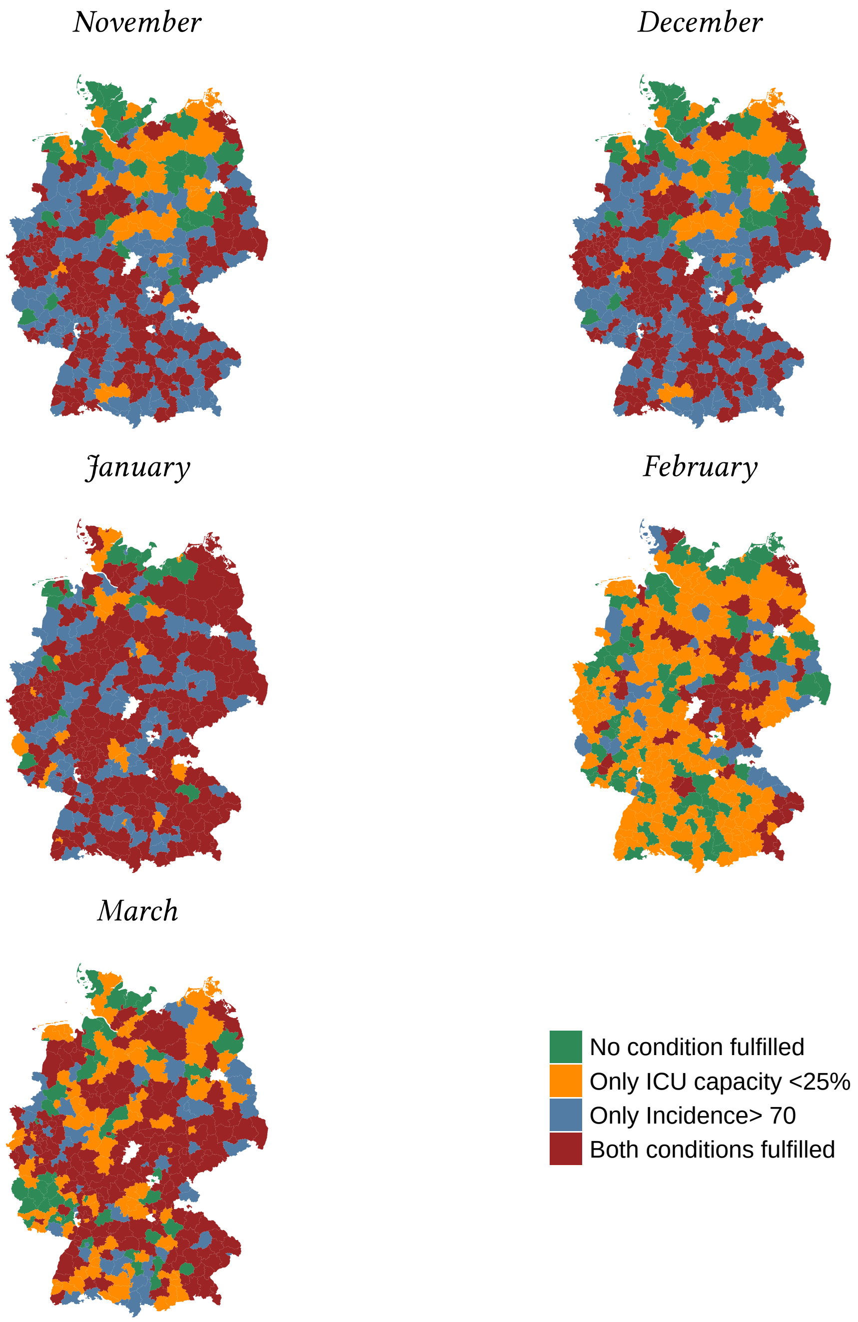
To illustrate the development of the pandemic situation and the respective ICU occupancy rates over time, we plot maps for the 17th of each month in our analysis sample, starting with November 2020 on the day before the new financial support scheme started. Counties in Figure 1 are colored to distinguish between four groups. Green indicates that counties have an incidence below 70 and more than 25% of the ICU capacity is free (no condition satisfied). Orange indicates that the ICU capacity is below 25% but

[8] There are 401 counties in Germany. There are some counties without hospitals or with hospitals without ICU units (Lankreis Fürth, Rhein-Pfalz-Kreis, Landkreis Coburg, Neustadt/Waldnaab). Two counties merged and the data reporting is, therefore, unclear (Wartburgkreis & Eisenach). Furthermore, we exclude Berlin due to data restrictions. Hospitals in the county Nienburg/Weser did not report ICU capacities on March 8th 2021. We impute the number of occupied and total beds with the data from one day before for this county.

incidence is below 70 (only ICU condition satisfied). Blue counties have an incidence above the threshold but more than 25% available ICU capacity. Red colored counties have both, incidence levels above the threshold and an below threshold share of free ICU beds.

The maps show that on the day before the emergency financing scheme started, there were counties neither fulfilling the condition of an incidence of 70 nor a low share of free ICU beds (green). The November map shows that most counties had already passed the reported Sars-Cov-2 incidence of 70 and hence would have been eligible for the scheme the next day – if their ICU occupancy was high enough. However, in particular the northern part of the country had several counties with low incidence levels. 49.23% of German counties had less than 25% free ICU beds. There is no clear geographical pattern with respect to the counties that had high or low ICU occupancy rates.

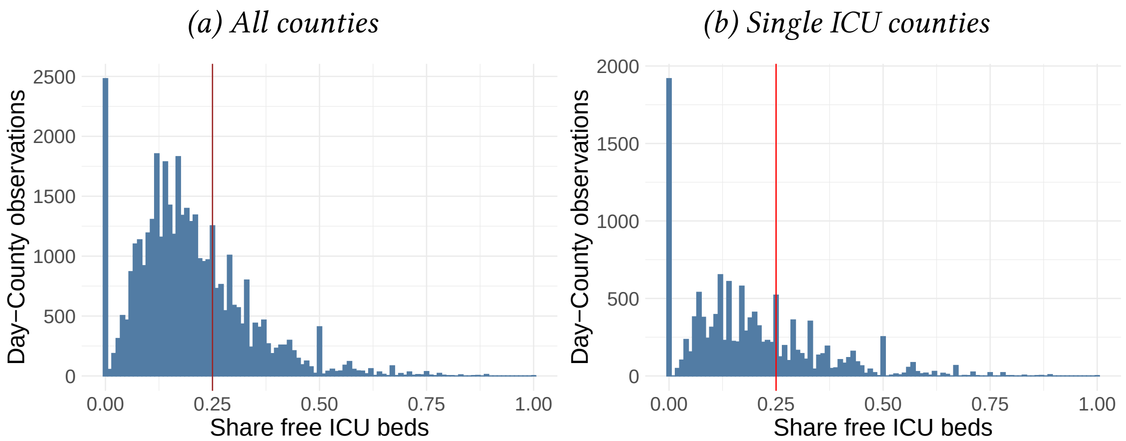
Figure 1: Incidence and ICU capacities over time



Notes: County-level depiction of reported incidences and reported free ICU capacities on every 17th between November 2020 and March 2021. ICU capacity refers to the number of total ICU beds reported by all hospitals in a county. Counties are marked in orange if less than 25% of the ICU capacity are free, incidence is the number of PCR-positive Sars-Cov-2 cases per 100.000 inhabitants in the last 7 days reported on the day without later corrections. Counties are marked blue if the incidence is higher than 70. Counties are marked in red if both conditions are met, green if no condition is met.

If hospitals strategically report their ICU capacity to be eligible for the emergency financing scheme, there should be heaping in the distribution of free ICU beds below the threshold of 25%. To get a first impression whether such a pattern occurs, we look at heaping in the univariat distribution of free ICU beds. We plot the frequency of each reported ICU availability rate in Figure 2. Both, in the distribution for all counties (Panel (a)) as well as in the distribution for counties that have only one hospital that operates ICU beds (Panel (b)), we see expected spikes for common shares (e.g. 25% and 50%).[9] There is, however, no clear heaping below the 25% eligibility threshold.

Figure 2: Descriptive analyses of reported ICU beds and incidences



Notes: The graphs show the distribution of day-county observations of the share of free ICU beds for all counties with incidences 70 or higher. Calculations based on observations from November 18th, 2020 - April 8th, 2021. In Panel (a), all counties are shown, in Panel (b) only county-day observation of counties with one ICU are included.

4.2 Event study analysis

We analyse the reaction in reported ICU capacities after the regional incidence level qualifies the hospitals in a county for financial support. In our analysis of strategic reporting of ICU capacities, we need to separate the effects of potential underreporting after a county fulfills the incidence condition of the financial support scheme and the simultaneous mechanical connection between rising incidence levels and increasing ICU occupancy. Therefore, we exploit the staggered timing of when the different counties crossed the relevant incidence of 70 at or after the introduction of the scheme on November 18th, 2020.

We use TWFE models to conduct an event study with the total number of reported ICU beds or share of free ICU beds in county c on day t, $Y_{c,t}$, as dependent variable. A county c is treated if the incidence condition for the financial support scheme is satisfied. Treatment hence means that the incidence in the county on date t is above the incidence threshold of 70 after the financial support scheme became effective on November 18th, 2020. Before this date, all counties are untreated. Counties which already had an incidence above 70 before the scheme was introduced are first treated on November 8th, 2020 and counties who cross the incidence threshold later on the first day with incidence

[9] While all hospitals with a number of ICU beds that is a multiple of four can have 25% free ICU beds, 11% free ICU beds is only possible for hospitals that have a multiple of nine ICU beds.

above 70. The 20 dummy indicators $D_{c,t,j}$ depict the days relative to treatment. Albeit the incidence needs to be higher than 70 for seven days to fulfill the extra compensation criterion, in our main specification, we posit that hospitals commence strategic reporting immediately upon reaching the incidence threshold. We check for other timing of treatment in our robustness section (see Section 4.5.5). We estimate ten leads and ten lags of the treatment indicator to inspect parallel trends pre-treatment and dynamic effects after the treatment took effect. The day before reaching the incidence of 70 is omitted as a reference group. The end points of the estimation ($j = -10, j = 10$) include not only ten days but ten or less/more days relative to the treatment, respectively, to saturate the model fully. Since these estimates are not comparable to the other relative treatment indicator estimates, they are omitted from the results. The estimated coefficients of the relative time indicators show the change in total reported ICU beds or the share of free ICU beds relative to the day before the incidence of 70 was reached. As control variables, we use county fixed effects, α_c, to control for time-invariant unobserved characteristics which influence the ICU capacity, i.e. the population density or the population structure. Additionally, we include calendar-day fixed effects, α_d, to control for unobserved time effects which influence the capacity of all counties, i.e. possible changes in reporting structures. Standard errors are clustered at county level.

$$Y_{c,t} = \sum_{j=-10}^{-2} \beta_j D_{c,t,j} + \sum_{j=0}^{10} \beta_j D_{c,t,j} + \alpha_c + \alpha_d + \epsilon_{c,t} \tag{1}$$

Recent literature explored that estimated average treatment effects from standard TWFE regressions may be biased, in particular when the treatment effects are heterogeneous and treatment can switch on and off (Goodman-Bacon, 2021). As incidence levels can drop below the threshold again (and hence counties switch from treated to untreated) and the treatment effect might be different for counties which are affected earlier compared to those later, the concerns about potential negative weighting apply to our analyses. Our setting is particular vulnerable to this issue since we observe very few never-takers, i.e. counties which never cross the threshold of 70. Therefore, we also present results from an alternative estimator proposed by de Chaisemartin and D'Haultfœuille (2020) (CH-TWFE) with correction weights. We estimate bootstrapped standard errors clustered at the county level.

Figure 3 shows the estimates for the classical TWFE estimation of Equation (1).[10] There is no systematic pre-trend in the number of total ICU beds and in the share of reported free beds in the days before counties crossed the incidence threshold - all lead co-

[10] Results for TWFE analyses are also summarized in Table A.1.

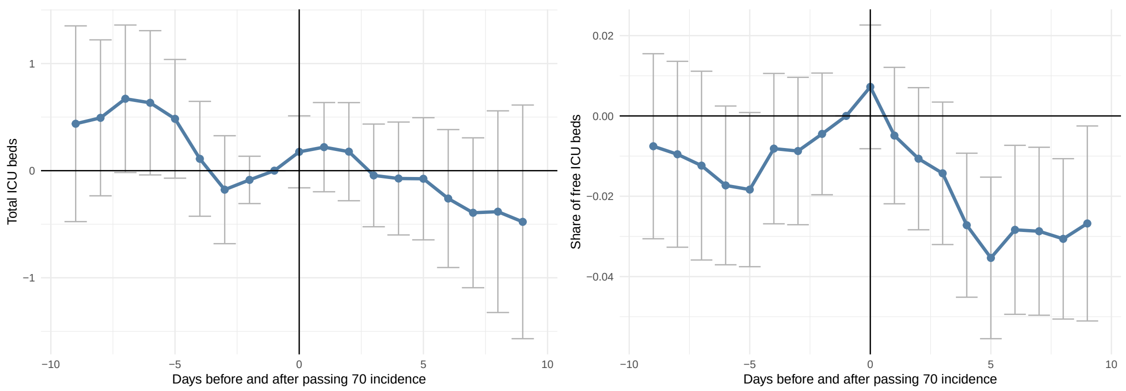
efficients are close to zero and insignificant. Therefore, parallel trends can be assumed. After counties crossed the incidence threshold, estimates for the change in reported ICU beds relative to untreated counties are close to zero for six days and then turn negative, albeit with huge confidence intervals. Hence, we do not find support for strategic reporting behavior in the days after reaching the incidence threshold. The event study for the share of free beds suggests a small, statistically significant decline in the share of available beds by three percentage points five days after the incidence threshold is crossed.

In Figure 4, we present the same event study as above, this time using the de Chaisemartin and D'Haultfœuille (2020) procedure. For the days leading up to the treatment, the adjusted estimates for the leads are around zero and insignificant for both outcome variables, the total ICU beds and the share of free ICU beds. For both outcomes, also the point estimates for the dynamic average effects are close to zero and statistically insignificant - although there seems to be a small downward trend. If hospitals try to hit the target of 25% empty capacity by shifting patients from regular wards to ICUs, one would not see changes in the total number of reported ICUs beds but in the share of free ICU beds. If hospitals want to hit this target without the cost of transferring patients and only by adjustments in bookkeeping, changes in the total number of ICU beds and the share of free ICU beds would be detectable. Our estimations do not show indications for neither of those adjustment mechanisms.

In line with the standard TWFE estimator, there are no indications for adjusted reporting behavior of ICU capacities on a large scale after counties fulfill the first criterion for financial support.

Figure 3: Event study - Standard TWFE

(a) Total reported ICU Beds *(b) Share of free ICU beds*



Notes: This graph plots estimates for a standard staggered event study. Blue circles show the dynamic treatment effects. The ribbons represent the 95% confidence intervals with standard errors clustered at county level. The total number of reported ICU beds in a county serves as outcome variable in Panel (a), the share of free ICU beds in a county in Panel (b). Estimations are based on day-county observations for 394 counties from November 1st, 2020 - April 8th, 2021.

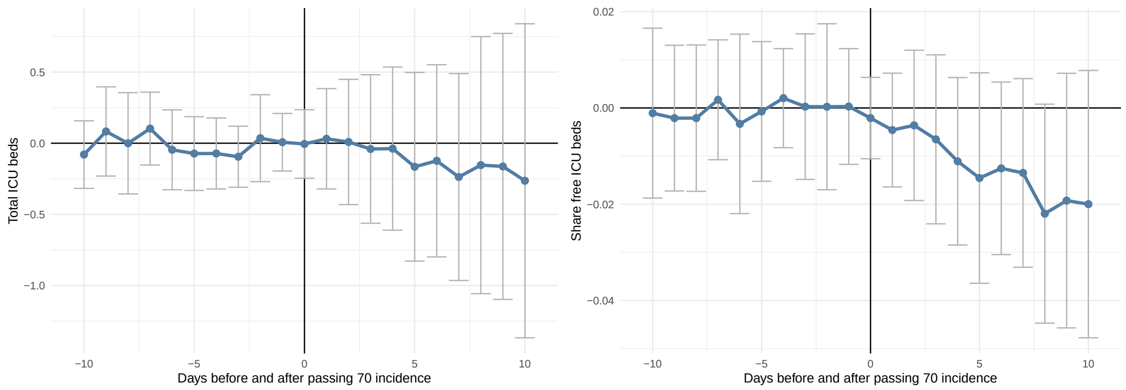
The conditions for financial support, including the free ICU capacity threshold of 25%, were applied to counties - not hospitals. Therefore, systematic underreporting of ICU capacities requires coordination between hospitals in a county. There are, however, counties with only one hospital that provides ICU beds. For these hospitals, the barrier of intra-county coordination does not apply. In these 95 counties, the hospital only needs to observe its own capacity, own occupied beds and can adjust the reporting to the registry without further coordination. We repeat our analyses for the subsample of counties with monopolistic hospitals. The results (see Figure 4, Panel (b)) show that also for this subgroup, there is no significant change in total ICU beds after the regional incidence is above the threshold of 70 and hence no indication for strategic reporting in this subgroup. Furthermore, the share of free ICU beds is not significantly different from zero albeit large confidence intervals.

There are multiple possible explanations why our results do not suggest any strategic reporting – despite the clear incentives to do so. First, there was no strategic reporting. Qualitative interviews with hospital management which we conducted during this research project actually indicate that hospitals were already working to capacity to deal with the increasing number of patients and new reporting obligations, leaving no resources for strategic reporting. Second, the amount of strategic reporting was too small to be detected by our empirical strategy. In Section 4.3, we show the results of our empirical approach for simulated data on which we perform different degrees of manipulation to show that underreporting can be detetcted in the data. Third, announcement effects might mask true reactions in reporting. In Section 4.4, we use coefficients of variation for the weeks before and after the introduction of the emergency financing scheme to detect changes in reporting over time. Fourth, only specific hospitals reported strategically and their effect is hidden in estimations with the full sample. In our heterogeneity analysis (Section 4.5), we show results for selective samples of hospitals. Lastly, hospitals needed to learn how to react to the incentives to manipulate reporting. Therefore, we analyze such learning effects by splitting the sample into two time periods according to the two Covid waves during our analysis in Section 4.5.2.

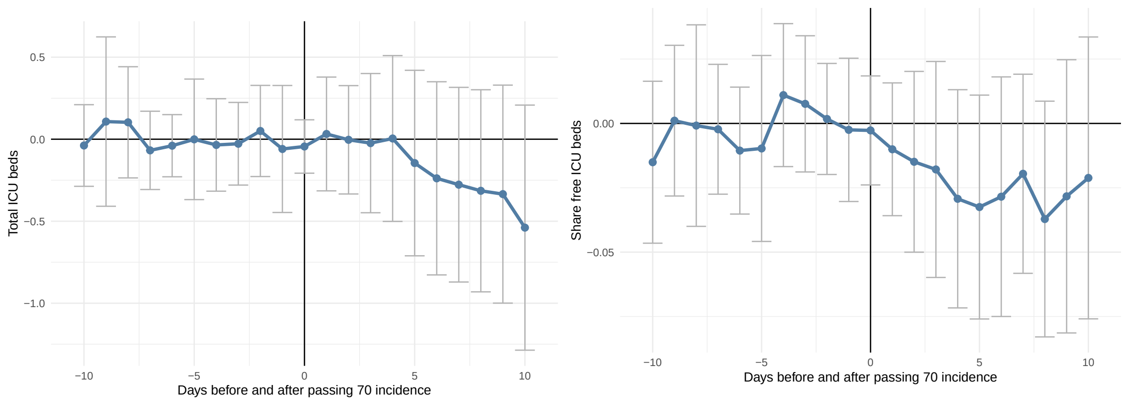
Figure 4: Event study - Chaisemartin/D´Haultfoeille TWFE

(a) All counties

(1) Total reported ICU Beds *(2) Share of free ICU beds*



(b) Single ICU counties



Notes: This graph plots the estimated β_j from Equation (1) using the CH-TWFE estimator. Blue circles show the dynamic treatment effects. The ribbons represent the 95% confidence intervals with bootstrapped standard errors clustered at county level. The total number of reported ICU beds in a county serves as outcome variable in Column (1), the share of free ICU beds in a county in (2). Estimations are based on day-county observations for 394 counties from November 1^{st}, 2020 - April 8^{th}, 2021 in the upper Panel (a), and for 133 single ICU counties and the same time period in the lower Panel (b). While the standard TWFE estimator uses all prior treatment periods as comparison, the CH-TWFE estimator employs only the day before, hence $j = -10$ and $j = 10$ are also displayed in the graph.

4.3 Manipulations in simulated data

In order to better understand what amount of strategic reporting would be necessary for our empirical analysis to identify an effect, we repeat our estimations with simulated data where we can modify the degree of manipulation. To generate our data, we employ the Cullen and Frey (1999) approach to identify what type of distribution best represents the actual number of free and total ICU beds in October and early November 2020 (before the support scheme depended on reported capacity).[11] This exercise indicates that the number of ICU beds is most similar to a negative binomial distribution. Hence, we use a negative binomial distribution to model the number of total ICU beds over counties on one day. We also estimate the occupancy rate in that manner.[12] Based on these initial distributions, we then use a data generating process that takes into account changes in the availability of beds depending on the actual incidence rate to generate a time series of ICU occupancy data for each county.

Given the generated distribution of ICU beds that resembles the actual distribution in October 2020, we can now add strategic reporting to the data. We implement manipulation of the random variable for total beds under the condition that misreporting only takes place in counties where a 30% or less reduction in total reported ICU beds is sufficient to receive financial support. We compute four scenarios: 1) No county misreports, i.e. no hospital is willing to adjust reporting figures, not even if it is financially beneficial, or 2) 25%, 3) 50% and 4) 75% of counties do so if underreporting would trigger the emergency financing. We base this on the assumption that hospitals in some counties are able and willing to adjust reporting behavior while others are not - and that this preference is consistent over time. This preference can root in two reasons. A hospital can have a preference for reporting accurately or hospitals in one county fail to collude. In Figure 5 in Column 1, we show histograms with the distribution of the free share of ICU beds under these scenarios. In the first row, we report the results of the event study with the simulated data but without manipulation. As expected, there is no heaping in the distribution of free ICU beds and the point estimates from the TWFE event studies are insignificant and close to zero. One can clearly see a jump in the free share of beds before 25% when possible manipulators adapt their reporting behavior (Rows 2, 3, and 4). In the TWFE analysis with simulated manipulation, we find clear effects when a high share of hospitals (counties) would decide to lower their number of reported ICU beds when it is financially beneficial. There is a negative point estimate on the first day of an incidence above 70 which is precisely estimated and highly significant. This effect is consistent over the following days. We repeat the manipulation process also with a 10% and a 20% or less reduction in ICU capacity and repeat the analyses. Especially for

[11] We search for the distribution and the descriptive parameters of this empirical distribution with a skewness-kurtosis plot probability distribution modeling the "random variable" total ICU beds. Skewness and kurtosis are known not to be robust. Considering the uncertainty of the estimated values of kurtosis and skewness from data, a nonparametric bootstrap is performed to re-estimate the parameters over and over again. Figure A.1 shows the Cullen and Frey (1999) graph.

[12] This way, we may underestimate the number of occupied beds for November since we generate random variables based on the distributions in October and early November. However, this only shifts the distribution downwards. For the analysis with simulated data, we cannot let them depend on incidence rates, so we accept this shift. Further, we set a minimum of ICU beds of four when generating the random variables based on the identified distributions.

the number of total beds, we can also see effects if we allow only for smaller reductions in the total number of ICU beds (see Tables A.2 and A.3). These results elicit confidence that underreporting on a moderate scale is detectable by our empirical approach.

4.4 Announcement effects

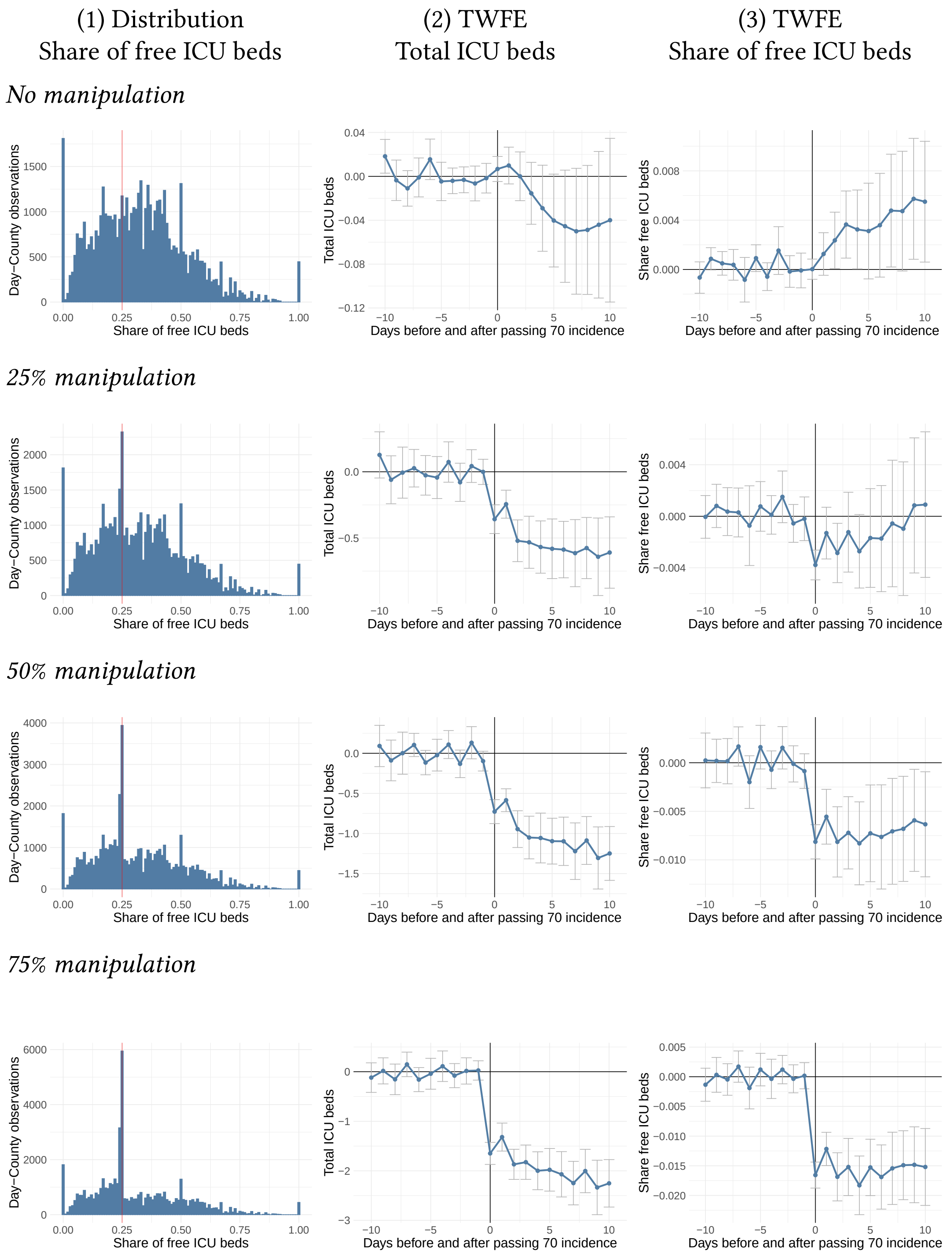
One possible explanation for absence of a significant reduction could be that hospitals reacted prior to the introduction of the new reimbursement rules already when the law was announced. If hospitals planned to behave strategically one may assume that hospitals reduce ICU capacity gradually as soon as it came to their knowledge that their free capacities would be a condition for payments. The draft legislation for new additional payments due to the pandemic has been first presented on November 3$^{\text{rd}}$, however, without the later important paragraph on conditions for reimbursements (Deutscher Bundestag, 2020b). On November 13$^{\text{th}}$, 2020 a large German newspaper mentioned first that new reimbursement mechanisms are planned to be tied to capacities (Geinitz, 2020). The official communication of capacity conditions was only on the 16th in a new legislation draft, hence two days before the law became effective (Deutscher Bundestag, 2020a). The short time frame makes gradual adjustments unlikely. To evaluate whether reporting behavior changed over time, we calculate the coefficient of variation for reported ICU beds in each county within every week. The coefficient of variation is a standardized measure of variance, in our case variance of reported total beds within a week. In other words, the higher the change in the number of total beds, the larger the coefficient. For each week from September 2020 to April 2021, we plot the average (and corresponding standard deviation) of the coefficient of variation over all counties. The results in Figure A.4 suggest that capacity changes are similar in early November compared to weeks after the introduction of the support scheme.

4.5 Heterogeneity analyses

4.5.1 High share of privately owned hospitals

Analogously to the main specification, we repeat the analyses for different county subgroups to evaluate whether the null finding is consistent across different groups of counties and not a result of averaging across groups. Firstly, we consider counties with a high share of private hospital owners, assuming that private owners have more efficient reporting units and might put more emphasis on profit optimization than public ones or not-for-profit charities. We consider in the analysis only counties with solely privately owned hospitals (36 counties). The results are similar to the previous ones (see Figure

Figure 5: Results from simulated data

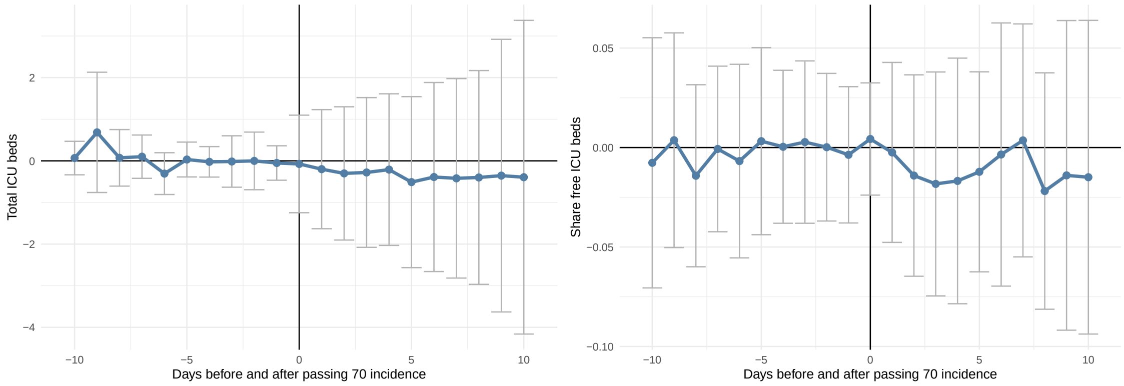


Notes: In Column (1), histograms show the distribution of the share of free ICU beds in the simulated data set. In Columns (2) and (3), we plot the estimated β_j from Equation (1) using the CH-TWFE estimator with generated data with (2) the total number of ICU beds as dependent variable and (3) the share of free ICU beds as dependent variable. Blue circles show the dynamic treatment effects. The ribbons represent the 95% confidence intervals with bootstrapped standard errors clustered at county level. The dependent variable is the number of total ICU beds in a county. Estimations are based on simulated day-county observations for 394 counties. In the different rows, different levels of manipulations are shown: 1) No county is willing to underreport, or 2) 25% , 3) 50% and 4) 75% of counties do so if beneficial. We assume misreporting only occurs in counties where reducing total ICU beds by 30% or less is necessary to receive financial support.

6) (see Figure 6). Also for counties with predominantly private hospitals there seems no manipulation detectable.

Figure 6: Event Study - Chaisemartin/D´Haultfoeille TWFE, high share private

(a) Total reported ICU Beds *(b) Share of free ICU beds*



Notes: This graph plots the estimated β_j from Equation (1) using the CH-TWFE estimator. Blue circles show the dynamic treatment effects. The ribbons represent the 95% confidence intervals with bootstrapped standard errors clustered at county level. The total number of reported ICU beds in a county serves as outcome variable in Panel (a), the share of free ICU beds in a county in Panel (b). Estimations are based on day-county observations for 36 counties with 100% privately owned hospitals from November 1st, 2020 - April 8th, 2021.

4.5.2 Pandemic waves

Furthermore, we separate the time period in the second and the third wave of the pandemic in Germany to check for heterogeneous time effects and learning effects. The second wave started from a very low summer plateau in 2020 at the end of September and built up quickly. The situation at ICUs of hospitals was comparatively relaxed in the beginning due to the low number of cases over the course of the summer but then worsened due to the fast rise in infections in December 2020. At the end of the second wave, infections decreased again but before infections reached low levels, the third wave built up again starting March 2021. The situation of ICU usage was very different since a lot of patients from the second wave still occupied beds. The RKI defines the time frame of the second wave from September 28th, 2020 until February 28th, 2021 and the third wave from 1st of March onwards (Tolksdorf et al., 2021). Hence, we repeat our TWFE analysis for the time frame until February 2021 and from March until June 2021. We find in neither time period indications for altered reporting behavior when the incidence threshold is reached in the following days (see Figure A.5 and Figure A.6).

4.5.3 Counties close to capacity threshold

The group of counties which are treated in our event study analyses is very heterogeneous. While some counties undercut the occupancy rate of 25% by far others have plenty of free ICU capacity. In order to focus on counties where changes in occupancy rates are likely to affect the eligibility of emergency compensation, we restrict our analyses to counties close to the 25% threshold. We therefore include counties which need to reduce the reported ICU capacity by at most three beds to become eligible compared to the day prior to the policy introduction, November 17th, 2020. This definition covers 77 counties. We suppose that adjusting reporting is simplest for this group and if gaming the system occurs, one should find effects for this group of counties. The event study results show no significant reactions for this group (see Figure A.7). Analogously to the simulation data analyses, we repeat our estimation strategy for all counties which could fall under the 25% free capacity rule when reducing the number of ICU beds by 10%, 20% or 30% compared to November 17th, 2020. Again, we cannot find a significant reduction un the number of total ICU beds or the share of free beds after the incidence threshold of 70 is crossed (see Figure A.8).

4.5.4 Counties with large ICU capacities

One could argue that adjusting reporting behavior is difficult for small ICUs since only large relative reductions are possible for them and it is more difficult to target the threshold of 75% occupied beds. Even though the capacities stem from different hospitals, we assume that marginal adjustment is easier in counties with a larger number of beds. We restrict the sample to counties with average ICU capacity in the analysis time frame of 50 and more ICU beds, which are 169 rather urban counties. We cannot find a significant reduction in reported capacities for this subsample (see Figure A.9).

4.5.5 Timing of fulfilling incidence condition

Technically, hospitals can receive compensation payments only when condition 1 for the support scheme, reaching an incidence of 70, is fulfilled for seven days in a row. For our main specification, we assume that as soon as the incidence threshold is reached, hospitals might start to report strategically, but it is also possible that they only adjust reporting when the seven days in a row of high incidences are reached. Therefore, we estimate our main specification again with a lagged treatment. Again, we find no significant reduction in reported beds with our TWFE analysis (see Figure A.10). The point estimates for the change in total ICU beds as well as the share of free ICU beds are even more persistent and closer to zero compared to the main specification event study.

5 Conclusion

We analyze how reported ICU capacity changed in reaction to an occupancy-based emergency financing scheme for German hospitals during the Coronavirus pandemic. During the second and third wave of the pandemic in Germany (November 2020 – May 2021), hospitals received extra funding to keep ICU capacities reserved for Covid-19 patients when the regional pandemic situation was severe – defined by high incidence rates and high ICU occupancy rates. While incidence rates are beyond hospitals' control, there is room for strategic reporting of available ICU capacities.

Strategic reporting denotes the situation when hospitals with an actual ICU occupancy rate slightly below the ICU occupancy threshold for extra financing (75% occupancy rate) would report a slightly higher ICU occupancy either by reducing the number of total beds or by keeping existing patients in the ICU longer. We employ different empirical strategies and cannot detect strategic reporting. We check for heaping in the distribution of total ICU beds around the incidence threshold and do not find any indications for manipulation. When we compare the reported number of ICU beds and share of free ICU beds around the eligibility threshold in an event study setting, our results show no discontinuity. Hence, hospitals do not alter reporting after crossing that threshold.

Using artificially generated data we simulate daily occupancy rates for each county under different assumptions for strategic reporting. We find that our empirical strategy would detect moderate amounts of such behavior. Nevertheless, our results might miss actual misreporting in some regions which is hidden in the idiosyncratic variance of ICU capacities in the other regions. This drawback stems from data availability limitations. The current county-level data is sufficient to detect reimbursement relevant strategic reporting but does not allow us to compare hospitals within a county or analyze decisions within hospitals (transfers, staffing levels) that lead to the reported capacity. Both in terms of research data availability as well as to improve patient allocation, data on occupancy rates needs to be easily accessible. Policymakers and hospital managers should work together to automate capacity reporting based on fully integrated hospital IT systems which would help to coordinate inpatient care not only in pandemic times.

Our key finding in this paper is that even though the emergency financing scheme leaves room for lucrative strategic behavior, such behavior did not occur on a detectable scale. This finding gives implications for future emergency support schemes. Easy-to-understand, simple support schemes can be a pragmatic solution since they can be implemented quickly and even if some actors might aim for excess profit, schemes are not necessarily exploited maliciously on a large scale.

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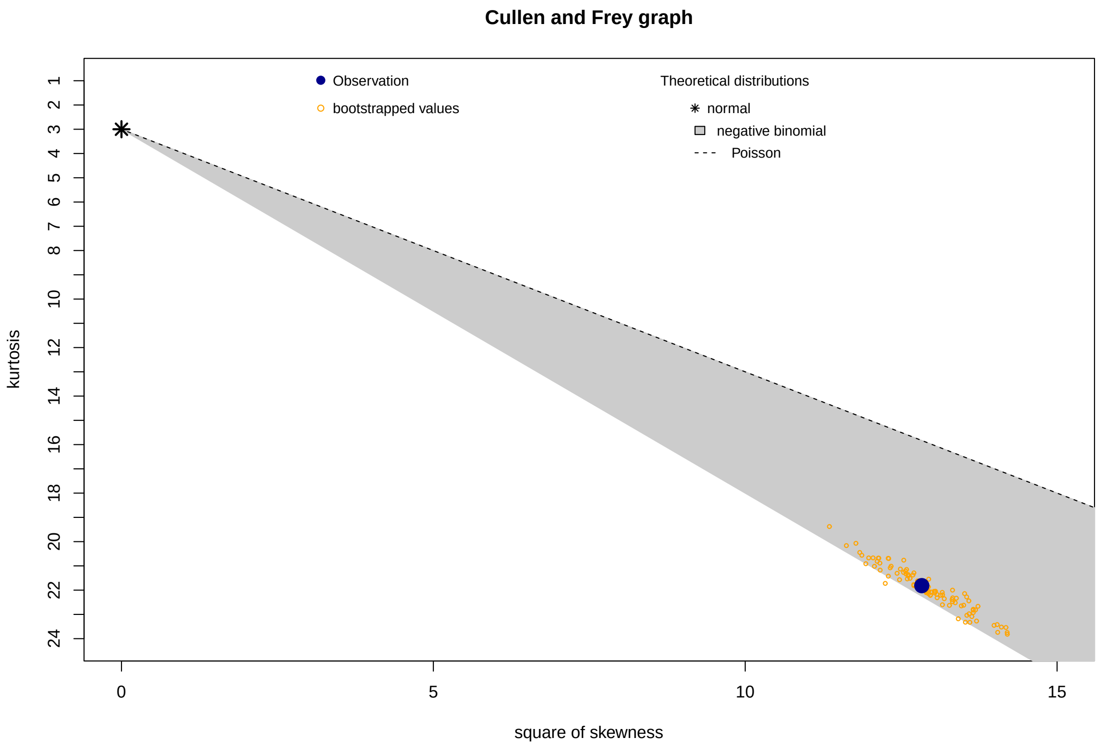
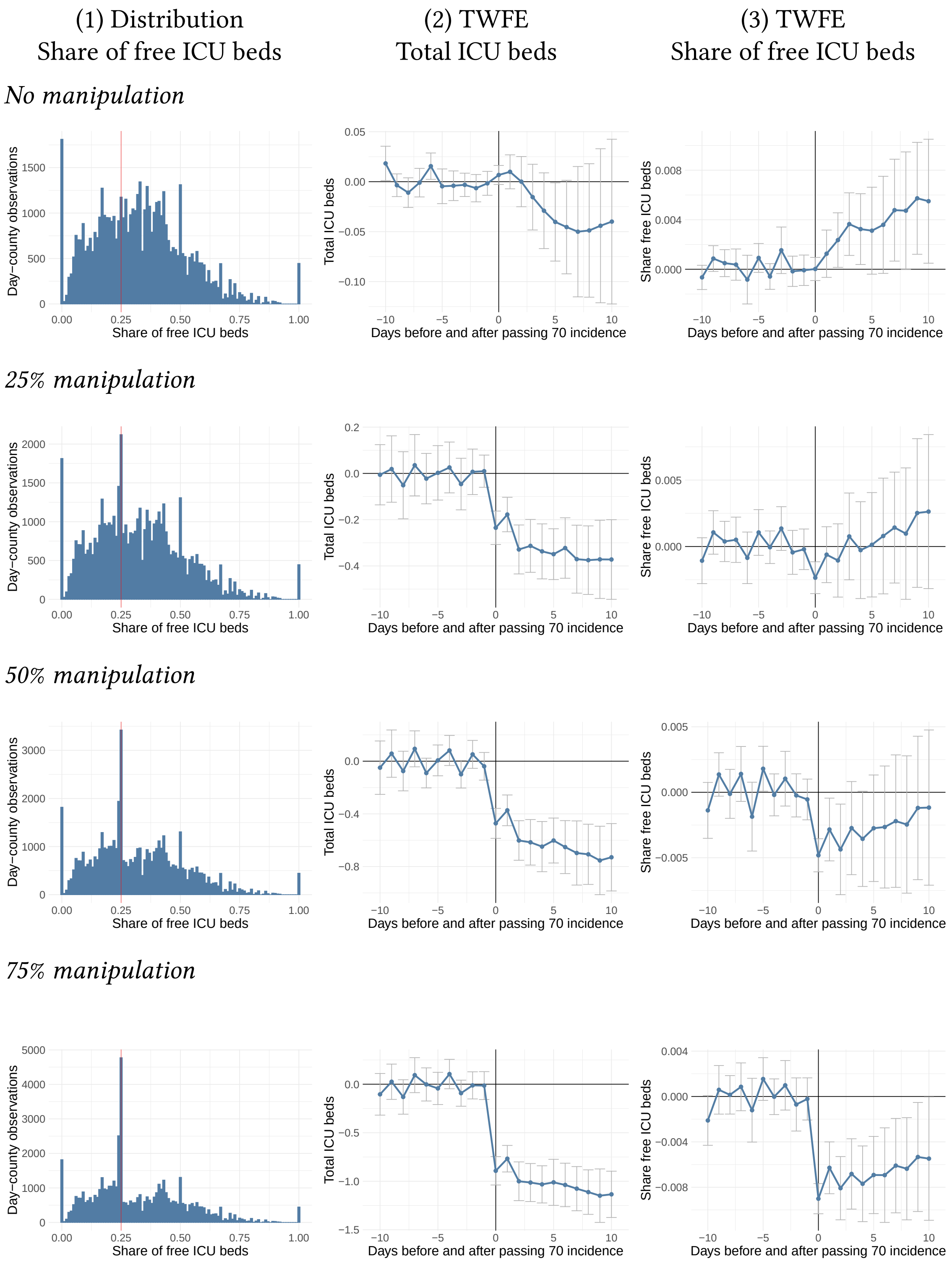
Appendix A - Additional tables and figures

Figure A.1: Cullen and Frey graph



Notes: Cullen and Frey (1999) graph for the distribution of reported ICU capacities from October 1st, 2020 - November 15th, 2020 (day before the announcement of the conditions for the financing scheme).

Figure A.2: Results from simulated data - 20% relative reduction in ICU beds

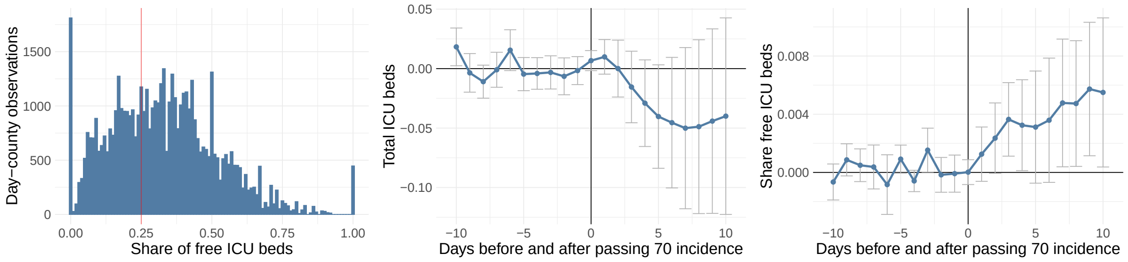


Notes: In Column (1), histograms show the distribution of the share of free ICU beds in the simulated data set. In Columns (2) and (3), we plot the estimated β_j from Equation (1) using the CH-TWFE estimator with generated data with (2) the total number of ICU beds as dependent variable and (3) the share of free ICU beds as dependent variable. Blue circles show the dynamic treatment effects. The ribbons represent the 95% confidence intervals with bootstrapped standard errors clustered at county level. The dependent variable is the number of total ICU beds in a county. Estimations are based on simulated day-county observations for 394 counties. In the different rows, different levels of manipulations are shown: 1) No county is willing to underreport, or 2) 25% , 3) 50% and 4) 75% of counties do so if beneficial. We assume misreporting only occurs in counties where reducing total ICU beds by 20% or less is necessary to receive financial support.

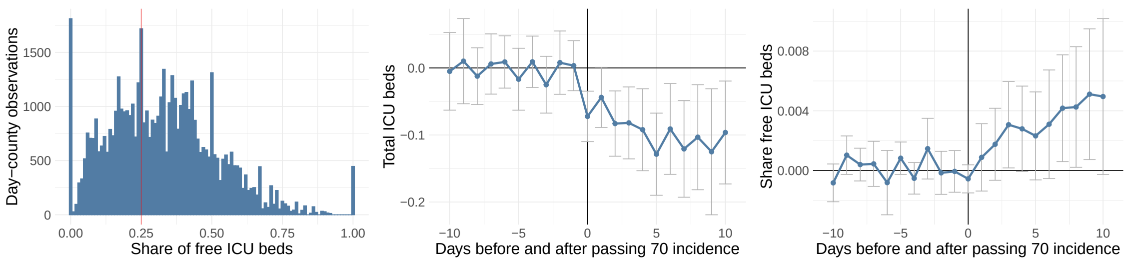
Figure A.3: Results from simulated data - 10% relative reduction in ICU beds

(1) Distribution Share of free ICU beds	(2) TWFE Total ICU beds	(3) TWFE Share of free ICU beds

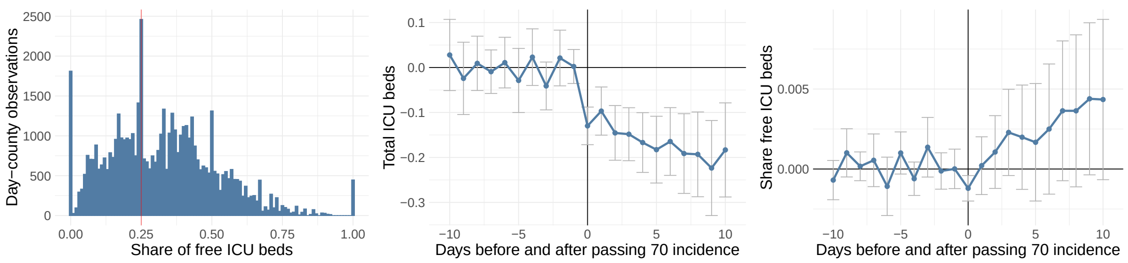
No manipulation



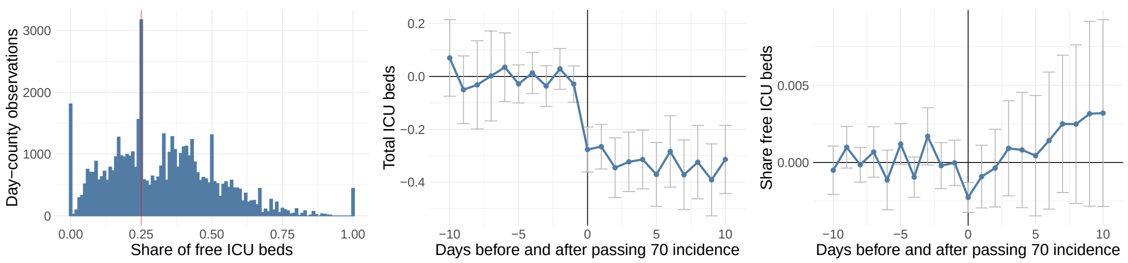
25% manipulation



50% manipulation

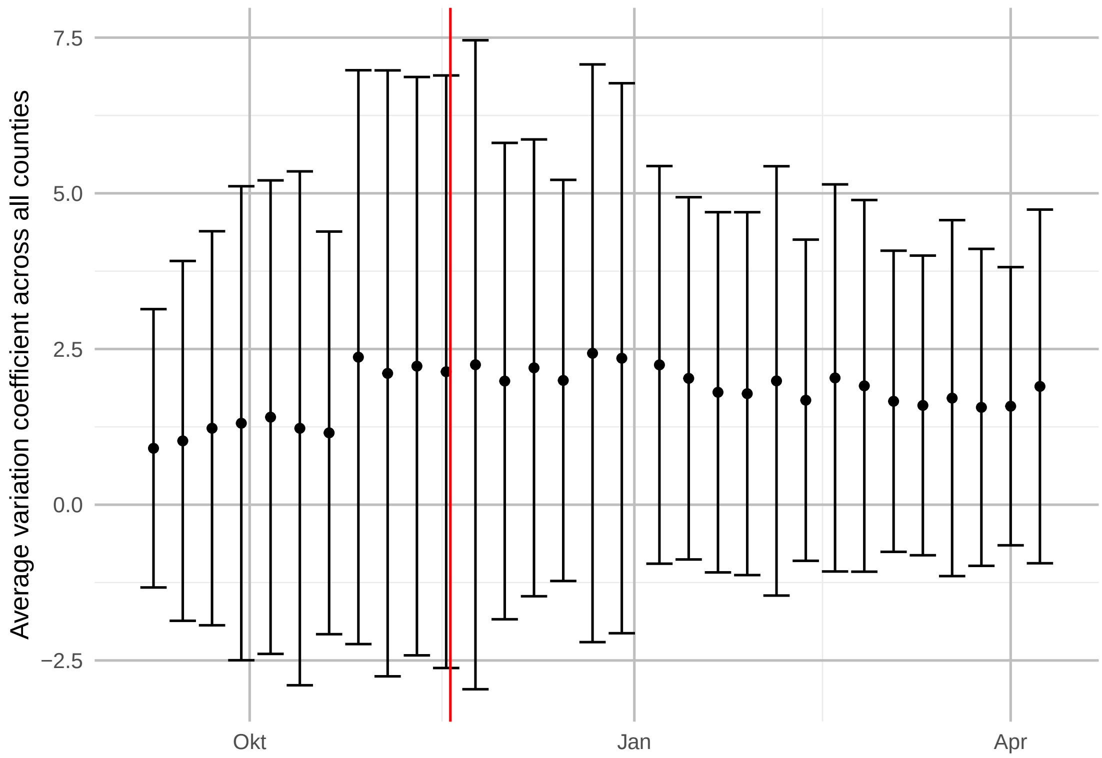


75% manipulation



Notes: In Column (1), histograms show the distribution of the share of free ICU beds in the simulated data set. In Columns (2) and (3), we plot the estimated β_j from Equation (1) using the CH-TWFE estimator with generated data with (2) the total number of ICU beds as dependent variable and (3) the share of free ICU beds as dependent variable. Blue circles show the dynamic treatment effects. The ribbons represent the 95% confidence intervals with bootstrapped standard errors clustered at county level. The dependent variable is the number of total ICU beds in a county. Estimations are based on simulated day-county observations for 394 counties. In the different rows, different levels of manipulations are shown: 1) No county is willing to underreport, or 2) 25% , 3) 50% and 4) 75% of counties do so if beneficial. We assume misreporting only occurs in counties where reducing total ICU beds by 10% or less is necessary to receive financial support.

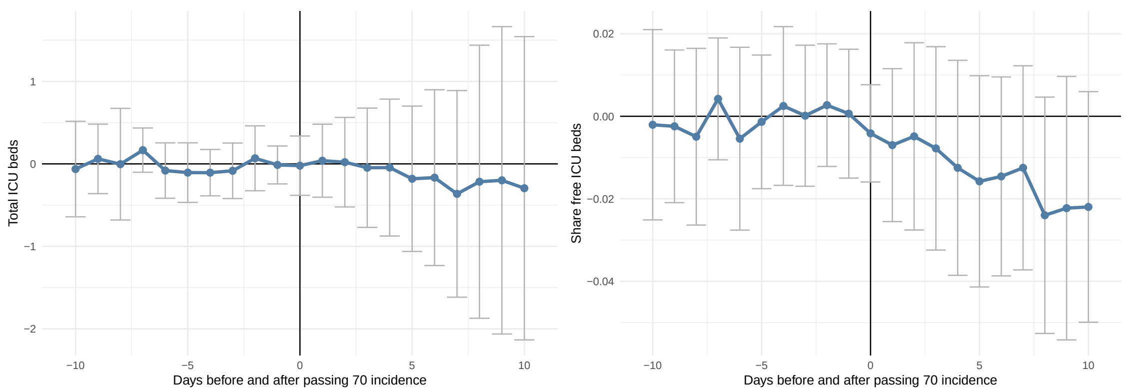
Figure A.4: Variation coefficient for reported ICU beds



Notes: This graph plots the variation coefficients for reported ICUs averaged across all counties on a given week from October 2020 to April 2021.

Figure A.5: Event study - Chaisemartin/D´Haultfoeille TWFE, second wave

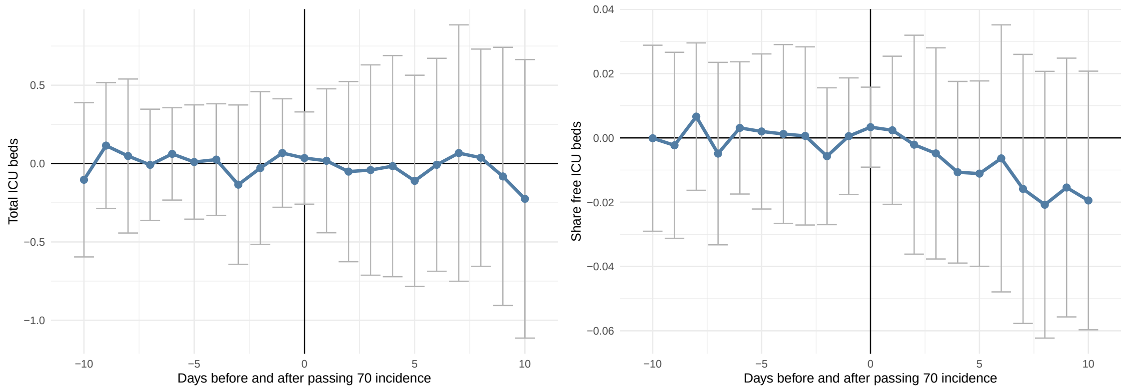
(1) Total reported ICU Beds *(2) Share of free ICU beds*



Notes: This graph plots the estimated β_j from Equation (1) using the CH-TWFE estimator. Blue circles show the dynamic treatment effects. The ribbons represent the 95% confidence intervals with bootstrapped standard errors clustered at county level. The total number of reported ICU beds in a county serves as outcome variable in Panel (1), the share of free ICU beds in a county in Panel (2). Estimations are based on day-county observations for 394 counties from November 1st, 2020 - February 28th, 2021.

Figure A.6: Event study - Chaisemartin/D´Haultfoeille TWFE, third wave

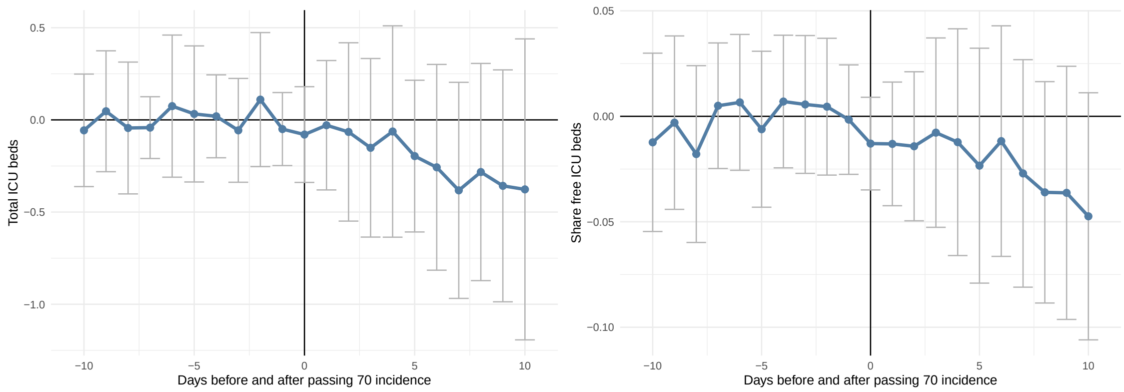
(1) Total reported ICU Beds *(1) Share of free ICU beds*



Notes: This graph plots the estimated β_j from Equation (1) using the CH-TWFE estimator. Blue circles show the dynamic treatment effects. The ribbons represent the 95% confidence intervals with bootstrapped standard errors clustered at county level. The total number of reported ICU beds in a county serves as outcome variable in Panel (1), the share of free ICU beds in a county in Panel (2). Estimations are based on day-county observations for 394 counties from March 1st, 2021 - April 8th, 2021.

Figure A.7: Event study - Chaisemartin/D´Haultfoeille TWFE, counties close to ICU threshold in absolut terms

(1) Total reported ICU Beds *(2) Share of free ICU beds*

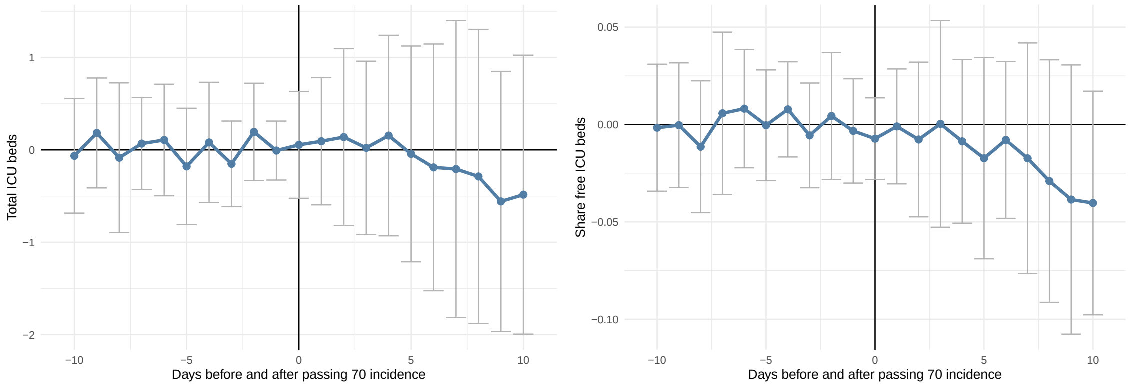


Notes: This graph plots the estimated β_j from Equation (1) using the CH-TWFE estimator. Blue circles show the dynamic treatment effects. The ribbons represent the 95% confidence intervals with bootstrapped standard errors clustered at county level. The total number of reported ICU beds in a county serves as outcome variable in Panel (1), the share of free ICU beds in a county in Panel (1). Estimations are based on day-county observations for counties which would have to change their reported capacity compared to Nov 17 2020 by three, two or one bed less to reach the 25% conditions (77 counties) from November 1st, 2021 - April 8th, 2021.

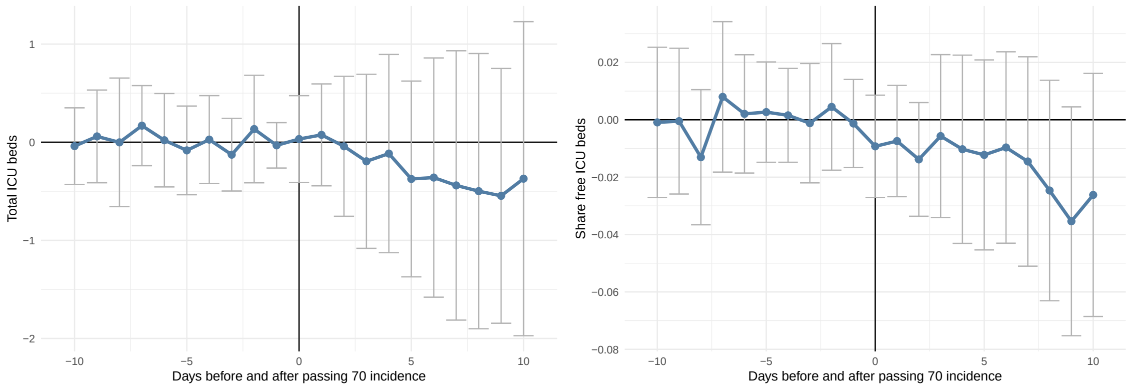
Figure A.8: Event study - Chaisemartin/D´Haultfoeille TWFE, counties close to ICU threshold in relative terms

(1) Total reported ICU Beds (2) Share of free ICU beds

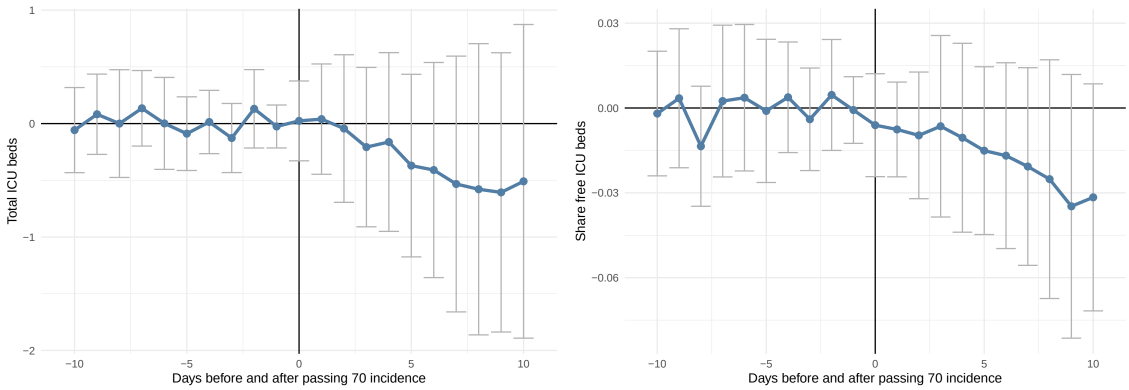
max. 10% reduction of ICU beds



max. 20% reduction



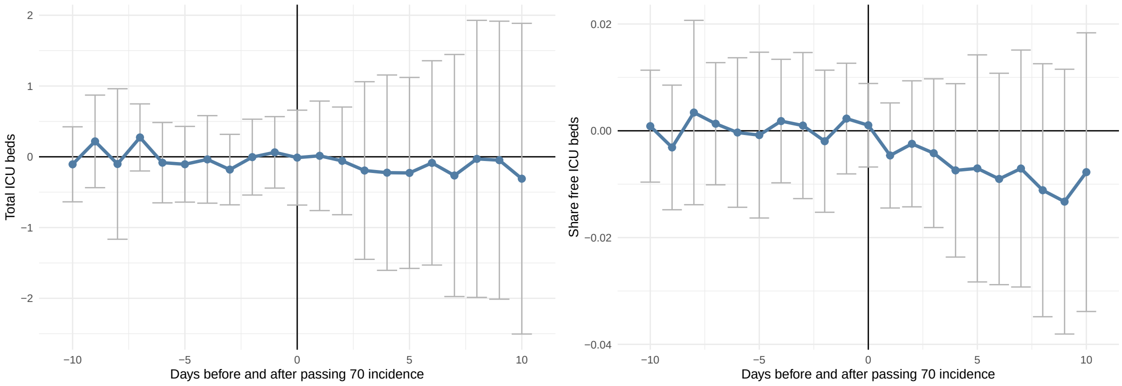
max. 30% reduction



Notes: This graph plots the estimated β_j from Equation (1) using the CH-TWFE estimator. Blue circles show the dynamic treatment effects. The ribbons represent the 95% confidence intervals with bootstrapped standard errors clustered at county level. The total number of reported ICU beds in a county serves as outcome variable in Panel (1), the share of free ICU beds in a county in Panel (1). Estimations are based on day-county observations for counties which would have to change their reported capacity compared to November 17th, 2020 by a reduction by 10%, 20% or 30% of ICU beds to reach the 25% conditions (75, 132, 158 counties respectively) from November 1st, 2020 - April 8th, 2021.

Figure A.9: Event study - Chaisemartin/D´Haultfoeille TWFE, large counties

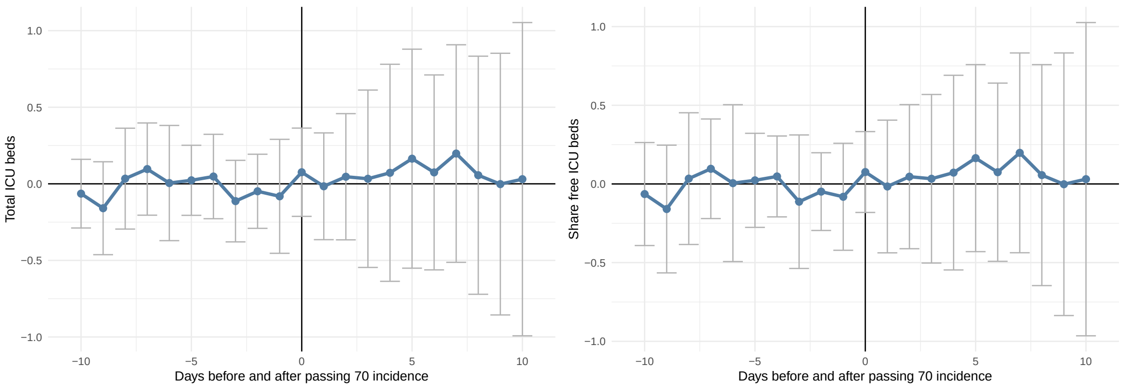
(1) Total reported ICU Beds *(2) Share of free ICU beds*



Notes: This graph plots the estimated β_j from Equation (1) using the CH-TWFE estimator. Blue circles show the dynamic treatment effects. The ribbons represent the 95% confidence intervals with bootstrapped standard errors clustered at county level. The total number of reported ICU beds in a county serves as outcome variable in Panel (1), the share of free ICU beds in a county in Panel (2). Estimations are based on day-county observations for counties with average ICU capacity in the analysis time frame of 50 and more ICU beds (169 counties) from November 1st, 2020 - Apr 08 2021.

Figure A.10: Event study - Chaisemartin/D´Haultfoeille TWFE, event 7 days lagged

(1) Total reported ICU Beds *(2) Share of free ICU beds*



Notes: This graph plots the estimated β_j from Equation (1) using the CH-TWFE estimator. Blue circles show the dynamic treatment effects. The ribbons represent the 95% confidence intervals with bootstrapped standard errors clustered at county level. The total number of reported ICU beds in a county serves as outcome variable in Panel (1), the share of free ICU beds in a county in Panel (2). Estimations are based on day-county observations for 394 counties from November 1st, 2020 - April 8th, 2021. Day 0 is the 7th day of an incidence higher than 70 in a county.

Table A.1: Summary table: Event study results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Standard	**CH**	**Monopoly**	**Wave 2**	**Wave 3**	**Close 0.25**	**Large ICU**
Event -10		-0.08	-0.0384	-0.0628	-0.1034	-0.0567	-0.1064
		(0.121)	(0.127)	(0.2954)	(0.2511)	(0.1557)	(0.2705)
Event -9	0.438	0.0826	0.1075	0.0604	0.1147	0.0468	0.2179
	(0.4661)	(0.16)	(0.2635)	(0.215)	(0.2051)	(0.1673)	(0.3337)
Event -8	0.4931	-6e-04	0.103	-0.0037	0.0482	-0.044	-0.1018
	(0.3714)	(0.1816)	(0.173)	(0.3454)	(0.2507)	(0.1824)	(0.5425)
Event -7	0.6713 *	0.1028	-0.0681	0.1666	-0.0084	-0.0419	0.2735
	(0.3513)	(0.1306)	(0.1218)	(0.1368)	(0.1813)	(0.0855)	(0.2418)
Event -6	0.6336 *	-0.0463	-0.0396	-0.0811	0.0619	0.0746	-0.0832
	(0.3436)	(0.1433)	(0.0967)	(0.1714)	(0.1504)	(0.1966)	(0.2896)
Event -5	0.484 *	-0.0728	-9e-04	-0.1061	0.0099	0.0322	-0.1056
	(0.2827)	(0.1323)	(0.1875)	(0.1843)	(0.186)	(0.1883)	(0.2729)
Event -4	0.1105	-0.0721	-0.035	-0.1066	0.0253	0.0194	-0.0367
	(0.2736)	(0.1272)	(0.1438)	(0.1434)	(0.1818)	(0.1147)	(0.3156)
Event -3	-0.1777	-0.095	-0.0277	-0.0842	-0.1345	-0.0568	-0.1809
	(0.2571)	(0.1095)	(0.1286)	(0.1717)	(0.2595)	(0.1436)	(0.254)
Event -2	-0.0862	0.0354	0.0502	0.0676	-0.0284	0.11	-0.0046
	(0.1127)	(0.1559)	(0.1418)	(0.2008)	(0.2487)	(0.1855)	(0.2734)
Event -1		0.0069	-0.0596	-0.0131	0.0673	-0.0499	0.0627
	(0)	(0.1031)	(0.1976)	(0.1174)	(0.1766)	(0.1011)	(0.2577)
Event +0	0.1757	-0.0053	-0.0444	-0.0218	0.0352	-0.0796	-0.0116
	(0.1714)	(0.1229)	(0.0831)	(0.1834)	(0.1502)	(0.1325)	(0.3421)
Event +1	0.2195	0.0312	0.032	0.0384	0.0178	-0.029	0.0138
	(0.2125)	(0.1799)	(0.177)	(0.2259)	(0.2343)	(0.179)	(0.3947)
Event +2	0.1773	0.0087	-0.0036	0.0205	-0.0513	-0.0654	-0.0576
	(0.2338)	(0.2246)	(0.1686)	(0.2769)	(0.2933)	(0.2468)	(0.3882)
Event +3	-0.0443	-0.0407	-0.0238	-0.0469	-0.0413	-0.1514	-0.1941
	(0.2445)	(0.2663)	(0.2166)	(0.3688)	(0.3424)	(0.2471)	(0.6404)
Event +4	-0.0732	-0.038	0.0044	-0.0449	-0.0163	-0.063	-0.2245
	(0.2689)	(0.2926)	(0.258)	(0.4233)	(0.36)	(0.2925)	(0.7043)
Event +5	-0.0756	-0.1658	-0.1454	-0.1808	-0.1104	-0.1964	-0.228
	(0.291)	(0.3383)	(0.2886)	(0.4496)	(0.344)	(0.21)	(0.6884)
Event +6	-0.2603	-0.1237	-0.2386	-0.1668	-0.0078	-0.2573	-0.0861
	(0.3286)	(0.3446)	(0.3005)	(0.5436)	(0.3467)	(0.2847)	(0.7366)
Event +7	-0.3931	-0.2376	-0.2773	-0.3638	0.0671	-0.3822	-0.2645
	(0.357)	(0.3709)	(0.3028)	(0.6389)	(0.4174)	(0.299)	(0.8725)
Event +8	-0.383	-0.154	-0.3146	-0.2165	0.0373	-0.2829	-0.0295
	(0.4803)	(0.461)	(0.3144)	(0.8445)	(0.3537)	(0.3005)	(0.9987)
Event +9	-0.4779	-0.1632	-0.3348	-0.1995	-0.082	-0.3578	-0.0479
	(0.5565)	(0.4769)	(0.3391)	(0.9507)	(0.4203)	(0.3209)	(1.0021)
Event +10		-0.264	-0.5392	-0.2955	-0.2249	-0.377	-0.3095
		(0.5631)	(0.3813)	(0.938)	(0.4535)	(0.4164)	(1.12)
N - Counties	394	394	95	394	394	77	169

Notes: This table shows results of performed TWFE analyses presented graphically in the paper with the outcome variable total ICU beds in a county. Column (1) shows the results of the standard TWFE analyses. Column (2) to (7) use the results from the CH-TWFE estimator. Column (2) show the main model, Column (3)the estimates for counties with one hospital, Columns (4) and (5) for the second and the third pandemic wave separately. Column (6) shows results only for counties which are close to the free capacity threshold of 25%. Column (7) limits the sample to counties with an ICU capacity which is on average at least 50 beds. Clustered standard errors on county level in brackets. Significance Levels: *** 0.01 ** 0.05 * 0.1.

Appendix B - Regression discontinuity analysis

Another way to exploit the variation of the reform is to assess whether there is a discontinuity on the incidence threshold of 70 for reported ICU beds. In such estimations, incidence can be the running variable where ICU occupancy reacts to crossing the 70 incidence threshold.

When we examine the power to detect manipulation using RDD estimations from our simulated data set, we find that even if a high amount of hospitals start to report strategically, the RDD estimation is not showing significant discontinuities. Due to the time averaging and the fast increase in incidences in the time, there is no effect in our simulated data (see Figure A.11). Therefore, we consider a regression discontinuity as unsuited for our research question.

For the sake of completeness, we nevertheless present results from RDD estimations using the actual data. A graphical analyses in Figure A.12 shows a small jump in reported beds at the threshold of 70 and the expansion of hospital beds seems to flatten around the cut-off of 70. A possible threat to the identification with an regression discontinuity design in this case is that due to time averaging effects and the disregarding of the timing of incidence threshold. This implies that strategic behavior would not be hardly detectable with such an design since the adjustment occurs only at the first days when crossing the incidence threshold from below, but for example not when crossing the threshold from above. Second, hospitals might not react instantaneously. Third, incidences increased fast potentially skipping a wide range of incidence levels which counteracts the underlying concept of disentangling a baseline trend and a potential discontinuity. Albeit these caveats, when estimating a regression discontinuity design, we use linear, quadratic and cubic terms, use a standard linear model as well as robust estimators as well as different bandwidth specifications. The estimation follows the Equation:

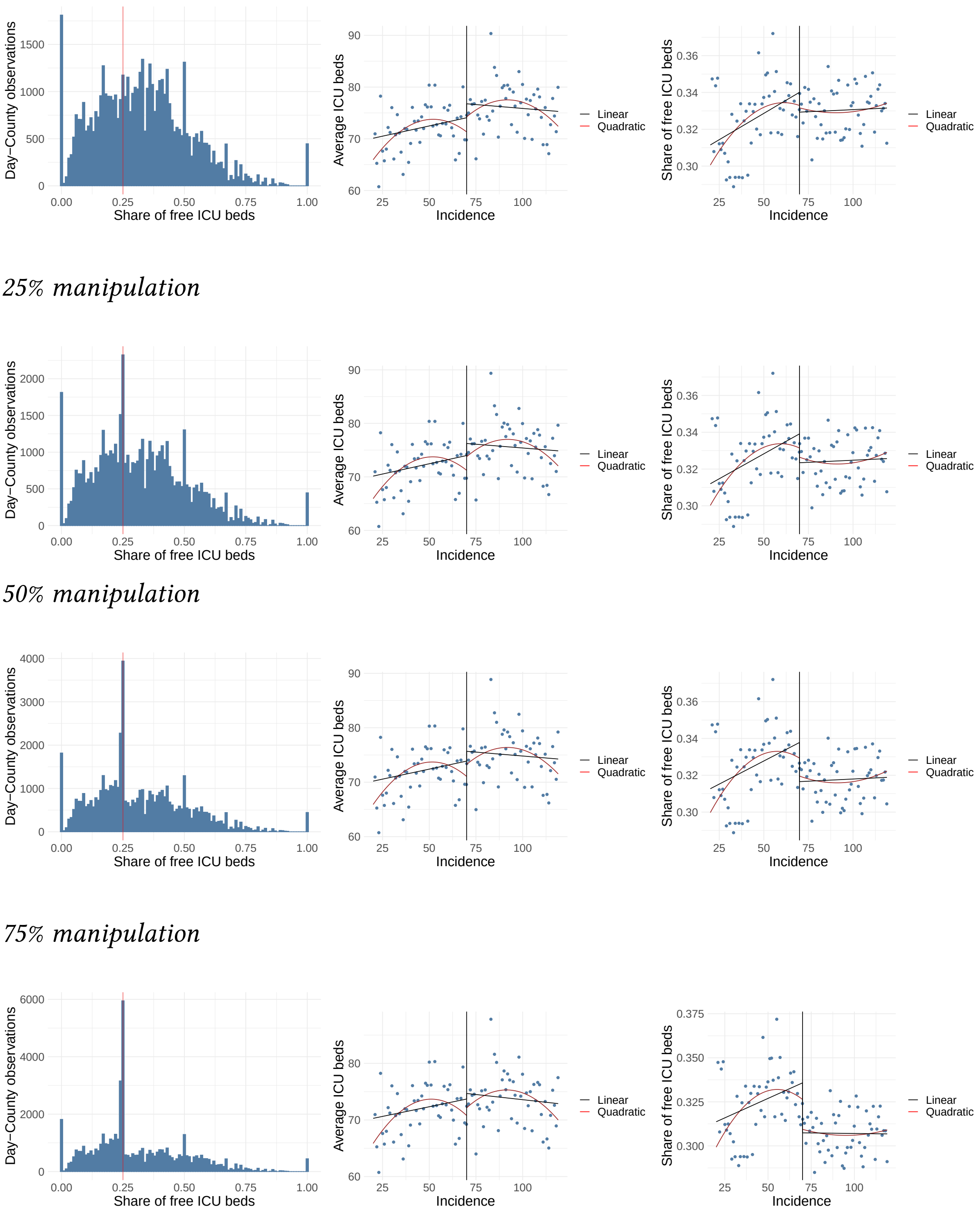
$$\begin{aligned} Y_{c,t} = \alpha + \beta D_{c,t} + f(Incidence_{c,t}) 1(Incidence < 70) + \\ f(Incidence_{c,t}) 1(Incidence \geq 70) + \gamma dow_{c,t} + \epsilon_{c,t} \end{aligned} \tag{2}$$

Where $Y_{c,t}$ is the reported number of ICU beds for a county c and a day t. $Incidence$ reflects the incidence on a day in a county and is the continuous assignment variable that determines the treatment D, which takes on the 1 when the incidence is above 70 and hence, the first condition for financial support is fulfilled. We use a first, second or third order polynomial of incidence $f(incidence_{c,t})$, separately on both sides of the cutoff 70. We control for the day of the week $dow_{c,t}$. The identification relies on the assumption

Figure A.11: Results for simulated data

(1) Distribution Share of free ICU beds	(2) RDD Total ICU beds	(3) RDD Share of free ICU beds

No manipulation



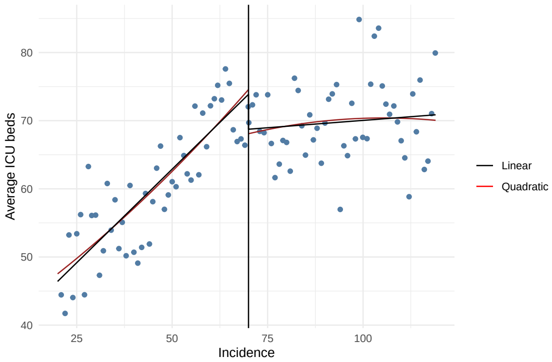
Notes: In Column (1), histograms show the distribution of the share of free ICU beds in the simulated data set. In Column (2), results of the RDD analyses (Equation (2)) with the generated data are displayed for a bandwidth of $\pm$ 50 with dependent variable total ICU beds. In Column (3), results of the RDD analyses (Equation (2)) with the generated data are displayed for a bandwidth of $\pm$ 50 with dependent variable share of free ICU beds. In the different rows, different levels of manipulations are shown: 1) No county is willing to underreport, or 2) 25% , 3) 50% and 4) 75% of counties do so if beneficial. We assume misreporting only occurs in counties where reducing total ICU beds by 10% or less is necessary to receive financial support.

that the hospitals cannot influence the reported incidence by a county. This is likely to hold since Covid tests are provided by several actors, data are gathered by public health authorities and every new patient in hospitals was tested for Covid anyways. In different specifications, we use varying bandwidths, namely ± 25, ± 50 around the incidence threshold and the full sample of all incidence rates (0-885). We employ robust estimators introduced by @calonicoRdrobust2017. We cannot find a significant jump at the incidence of 70 in reported beds in any specification (see Tables A.2 and A.3 for all specifications). We read this estimation as indication that there was no clear underreporting of ICU beds at the incidence threshold of 70. However, further analyses is necessary since the increasing of beds seems to stop somewhere around the cutoff of 70. The share of free ICU beds serves as an alternative dependent variable. There is a clear negative correlation between incidence levels and the share of free ICU beds over the entire period. This stems from the increasing number of patients on ICUs when more people are sick due to Covid. Also in this alternative measure, we do not see a clear cut at the threshold of 25% of free ICU capacity.

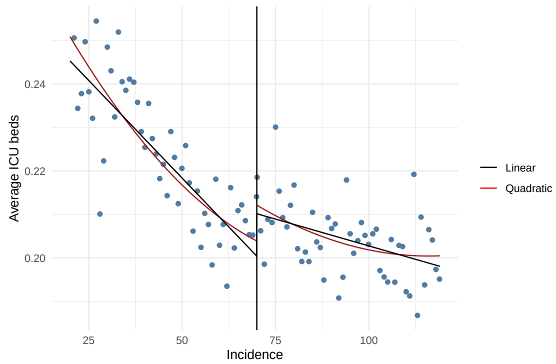
Figure A.12: Regression dicountinuity design

(a) All counties

(1) Total ICU beds

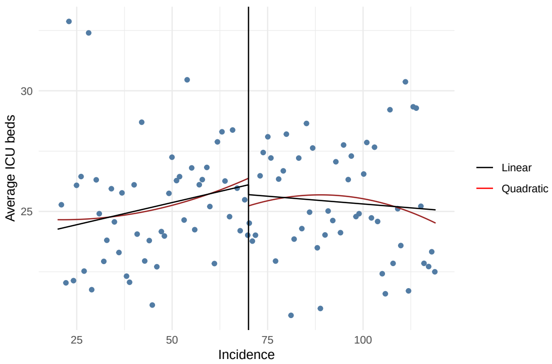


(2) Share of free ICU beds

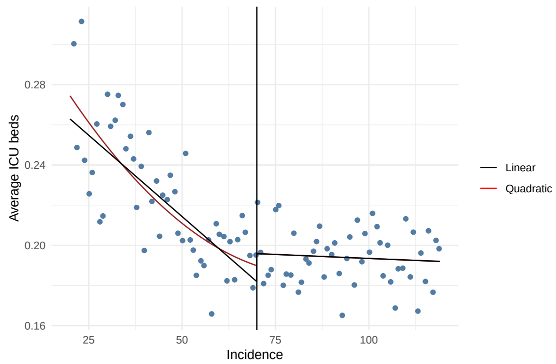


b)Single ICU counties

(3) Total ICU beds



(4) Share of free ICU beds



Notes: This graph plots the observed number of ICU beds per incidence level in binned means constructed with a mimicking variance method (esmv method of rdplot) together with a fitted line of both sides of the threshold allowing for linear and quadratic relations. Panel (a) contains all counties with incidences between 20 and 119 from November 18$^{\text{th}}$, 2020 to April 4$^{\text{th}}$, 2021, in Panel (b) the sample is restricted to counties with only one hospital with ICU. in the left graphs (1, 3) the total number of ICU beds serves as dependent variable. In the right graphs (2, 4) the share of free ICU beds.

Table A.2: Resgression discontinuity results

	Linear		Quadratic		Cubic	
Model	**Coefficient**	**p-value**	**Coefficient**	**p-value**	**Coefficient**	**p-value**
Total ICU beds // Panel (a) - All Incidences						
Conventional	3.03	0.67	4.05	0.59	8.05	0.3
Bias-Corrected	6.65	0.36	6.05	0.42	9.17	0.23
Robust	6.65	0.37	6.05	0.42	9.17	0.26
N	55948		55948		55948	
Panel (b) - Incidences with Bandwidth 50 around 70						
Conventional	4.98	0.51	5.65	0.45	5.1	0.56
Bias-Corrected	7.77	0.3	7.42	0.32	3.45	0.69
Robust	7.77	0.32	7.42	0.32	3.45	0.71
N	33157		33157		33157	
Panel (c) - Incidences with Bandwidth 25 around 70						
Conventional	4.05	0.6	0.52	0.95	-0.76	0.93
Bias-Corrected	2.04	0.79	-1.43	0.87	-1.97	0.83
Robust	2.04	0.8	-1.43	0.88	-1.97	0.84
N	19095		19095		19095	
Share of free ICU beds //Panel (d) - All Incidences						
Conventional	-0.01	0.28	-0.01	0.27	-0.01	0.13
Bias-Corrected	-0.01	0.11	-0.01	0.16	-0.01	0.08
Robust	-0.01	0.15	-0.01	0.18	-0.01	0.1
N	55948		55948		55948	
Panel (e) - Incidences with Bandwidth 50 around 70						
Conventional	-0.01	0.33	-0.01	0.12	-0.01	0.13
Bias-Corrected	-0.01	0.17	-0.01	0.07	-0.01	0.1
Robust	-0.01	0.2	-0.01	0.1	-0.01	0.12
N	33157		33157		33157	
Panel (f) - Incidences with Bandwidth 25 around 70						
Conventional	-0.01	0.15	-0.01	0.37	0	0.92
Bias-Corrected	-0.01	0.08	-0.01	0.47	0	0.87
Robust	-0.01	0.12	-0.01	0.52	0	0.88
N	19095		19095		19095	

Notes: This table shows results of the regression discontinuity design in Equation (2) with dependent variable total ICU beds in Panel (a), (b) and (c) and dependent variable share of free ICU beds in Panel (d), (e) and (f). Conventional refers to a classic OLS approach, Bias-Corrected and Robust refer to adjusted estimators introduced by Calonico et al. (2017). In Column (1), we report estimates for a linear specification, in Column (2), we allow for a quadratic, in Column (3) for a cubic relationship. The table shows results for all incidence levels (0-885) in Panel (a), a bandwidth of ± 50 around the incidence cutoff of 70 in Panel (b) and a bandwidth of ± 25 in Panel (c). Significance Levels: *** 0.01 ** 0.05 * 0.1.

Table A.3: Resgression discontinuity results - Single ICU counties

	Linear		Quadratic		Cubic	
Model	**Coefficient**	**p-value**	**Coefficient**	**p-value**	**Coefficient**	**p-value**
Total ICU beds // Panel (a) - All Incidences						
Conventional	1.01	0.6	1.26	0.54	0.52	0.81
Bias-Corrected	0.96	0.62	0.9	0.66	0.05	0.98
Robust	0.96	0.64	0.9	0.68	0.05	0.98
N	18886		18886		18886	
Panel (b) - Incidences with Bandwidth 50 around 70						
Conventional	1	0.61	1.19	0.57	0.88	0.68
Bias-Corrected	0.87	0.66	1.3	0.53	0.86	0.69
Robust	0.87	0.68	1.3	0.55	0.86	0.7
N	10345		10345		10345	
Panel (c) - Incidences with Bandwidth 25 around 70						
Conventional	1.08	0.58	1.08	0.62	2.09	0.53
Bias-Corrected	1.06	0.59	0.98	0.65	2.82	0.4
Robust	1.06	0.61	0.98	0.68	2.82	0.46
N	5774		5774		5774	
Share of free ICU beds //Panel (d) - All Incidences						
Conventional	-0.02	0.13	-0.02	0.06	-0.03	0.04
Bias-Corrected	-0.02	0.06	-0.03	0.03	-0.03	0.03
Robust	-0.02	0.09	-0.03	0.05	-0.03	0.04
N	18886		18886		18886	
Panel (e) - Incidences with Bandwidth 50 around 70						
Conventional	-0.02	0.13	-0.02	0.1	-0.02	0.11
Bias-Corrected	-0.02	0.06	-0.02	0.08	-0.03	0.1
Robust	-0.02	0.08	-0.02	0.12	-0.03	0.14
N	10345		10345		10345	
Panel (f) - Incidences with Bandwidth 25 around 70						
Conventional	-0.03	0.05	-0.04	0.05	-0.05	0.08
Bias-Corrected	-0.03	0.02	-0.04	0.04	-0.05	0.05
Robust	-0.03	0.04	-0.04	0.07	-0.05	0.08
N	5774		5774		5774	

Notes: This table shows results of the regression discontinuity design in Equation (2) with dependent variable Total ICU beds in Panel (a), (b) and (c) and dependent variable Share of free ICU beds in Panel (d), (e) and (f). Conventional refers to a classic OLS approach, Bias-Corrected and Robust refer to adjusted estimators introduced by Calonica et al. (2017). In Column (1), we report estimates for a linear specification, in Column (2) ,we allow for a quadratic, in Column (3) for a cubic relationship. The table shows results for all incidence levels (0-885), a bandwidth of ± 50 around the incidence cutoff of 70 and a bandwidth of ± 25. The sample contains counties with only one hospital with ICU. Significance Levels: *** 0.01 ** 0.05 * 0.1.

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