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Supply Constraints and Negative Selection: Evidence from Mental Healthcare Markets

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Abstract

Despite universal healthcare coverage and clinical guidelines recommending psychotherapy after psychiatric hospitalization, only 26% of German patients receive it, and paradoxically, the sickest patients are least likely to get treatment. Using administrative claims data, we investigate whether increasing psychotherapy supply addresses this misallocation. For identification, we exploit quasi-random variation from Germany's therapist license allocation system. A one standard deviation higher supply raises therapy uptake by 10%, modestly reduces waiting times, and lowers patient search frictions, but does not alter the composition of therapy recipients. These findings challenge the assumption that healthcare capacity constraints affect all patients equally.

JEL-Classification: I11, I18, H51, R53
Keywords: Mental health, Healthcare markets, Waiting time

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1 Introduction

One in five individuals worldwide suffers from mental illness. The associated reduction in productivity, increased healthcare costs, and premature mortality incur costs between \$5–\$10 trillion per year (Arias et al., 2022). Despite the availability of evidence-based treatments, such as psychotherapy, a paradox has emerged: Even in high-income countries with universal healthcare, most individuals experiencing mental health hospitalizations do not receive follow-up psychotherapy (Wang et al., 2007), and those receiving treatment may not be the ones needing it most (Olfson et al., 2025).[1]

The low treatment uptake may be partly due to government-imposed limits on the supply of psychotherapy. By contrast, even in countries with less regulation, supply shortages prevail. For example, almost half of the US population lives in a designated mental health care shortage area (Health Resources and Services Administration, 2024), and Medicare beneficiaries face median waiting times exceeding 100 days in many regions. The adverse health consequences of these supply shortages are frequently discussed in public discourse.[2] Accordingly, policymakers aim to alleviate the under-treatment of mental illness through supply-side interventions.[3] Recent evidence, however, challenges the idea that low treatment uptake is driven by provider shortages (Cronin et al., 2024; Roth et al., 2024), making it uncertain whether increasing mental healthcare supply achieves its desired goal.

This paper investigates how increasing mental healthcare supply affects treatment allo-

[1]Medical treatment guidelines recommend psychotherapy as a follow-up treatment for all patients after hospitalization due to mental illness (DGPPN and BÄK and KBV and AWMF, ed, 2017).

[2]See The Guardian (2022) for an example from the US and Sozialverband VdK (2024) for Germany.

[3]Leading examples are the US Medicare mental health workforce expansion under the *Consolidated Appropriations Act* and the UK *Improving Access to Psychological Therapies* program.

cation. In particular, we identify whether higher psychotherapy supply primarily reduces waiting times for existing patients, increases the number of patients treated, or changes who receives treatment. Our empirical analysis builds on daily administrative claims data on all patients insured by Germany's largest public health insurance provider, that were hospitalized for mental illness in 2017. Patients with a recent psychiatric hospitalization are an ideal population to study the effects of mental healthcare supply, since medical guidelines recommend psychotherapy for all patients, yet only few receive the appropriate treatment.

For identification, we leverage variation in local outpatient therapy supply arising from Germany's unique licensing system, where counties receive fixed allocations of therapy licenses based on past healthcare demand. These licenses cap supply because only licensed providers can bill the public health insurance. We exploit that regions receiving the same number of licenses per capita differ in their therapy supply because multiple practitioners can share one license. Per-license therapy supply is, on average, 50% higher if the license is shared. We thereby impose the identifying assumption that a practitioner's choice to obtain a shared license is unrelated to factors determining patients' health. The assumption would be violated if practitioners systematically prefer shared licenses whenever patients' access to healthcare is poor. We investigate its plausibility by showing that license-sharing is orthogonal to patients' average case severity, their past uptake of psychotherapy, and their take-up of physical and non-therapeutic healthcare at any point in time. For robustness, we replicate our results using a local congestion design based on the recent literature (Costantini, 2025; Prudon, 2025; Williams and Bretteville-Jensen, 2024), which produces quantitatively analogous results.

Descriptively, we document a pattern of treatment misallocation in mental healthcare markets. Despite universal coverage and clinical guidelines recommending psychotherapy for all patients following psychiatric hospitalization, only 26% receive any therapy within one year of discharge. Further, we find systematic negative selection. Patients with the highest predicted readmission risk, hence those who would arguably benefit most from treatment, are least likely to receive it.[4] Among those receiving psychotherapy after their psychiatric hospitalization, patients with high readmission risk face the longest waiting times.

Introducing higher therapy supply thereby improves mental health care utilization as recommended by medical guidelines. A one standard deviation (SD) higher therapy supply induced by Germany's licensing system raises the uptake of psychotherapy after psychiatric hospitalization by 2-2.6 pp, or 10% relative to the sample mean, without crowding out pharmaceutical treatment. On the intensive margin, waiting times decrease by 3 to 4 days compared to a median of 99 days, and the number of days between individual therapy sessions shrinks marginally. Moreover, the share of patients receiving psychotherapy in their county of residence increases by 8%, reflecting an inverse relation between supply capacity and patients' search effort necessary to receive treatment. Still, higher therapy supply does not correct the aforementioned misallocation. Supply-sensitive patients receiving therapy due to higher treatment capacity do not differ in their characteristics from patients receiving treatment at low capacity levels.

Existing research on healthcare supply suggests that increasing provider availability primarily improves access through reduced waiting times, with patients receiving treatment

[4]The selectivity of patients receiving certain types of healthcare also exists outside the market for mental healthcare, see, e.g., Einav et al. (2020) or Oster (2020).

according to medical need (Abramson et al., 2024). This view is supported by empirical work finding that supply shortages create treatment delays with far-reaching consequences (Costantini, 2025; Prudon, 2025; Oparina et al., 2024; Reichert and Jacobs, 2018; Williams and Bretteville-Jensen, 2024). Treatment uptake, in contrast, is considered inelastic to healthcare capacity, e.g., due to patients' reluctance to initiate therapy (Cronin et al., 2024; Roth et al., 2024). In addition, the literature has paid limited attention to selection mechanisms that can operate in professional service markets where providers exercise discretion over patient acceptance (Desai et al., 2009; Gandhi, 2020).

The results of this paper challenge the way we think about expanding healthcare supply. Despite universal insurance coverage, psychotherapy take-up is highly supply-sensitive among individuals for whom therapy is strongly recommended by treatment guidelines. These findings reveal that patients' willingness to receive talk therapy is generally high, yet non-monetary market frictions hinder individuals from receiving a guideline-consistent treatment. Increasing therapy supply thus partly alleviates the prevalent under-treatment of mental illness. However, we find that marginal increases in supply do not reverse what we call *negative selection*: the inverse relation between the risk of relapse and treatment uptake. Individuals receiving therapy due to marginal increases in supply are still characterized by lower case severity. This finding contradicts the core assumption underlying most healthcare workforce policies and theoretical models of professional service markets, that those with the highest need will be served first. We make the argument that capacity extensions alone are insufficient to reverse negative selection if excess demand is high. Only once the pool of supply-sensitive lower-risk patients is sufficiently exhausted do higher-risk patients benefit from supply expansions. This finding may be generalized to other service markets with provider discretion and excess demand, such as those for public childcare or nursing home care. Jessen et al. (2020), for example, find that a childcare capacity extension was not disproportionally allocated to migrant families, who are actively discriminated against by childcare providers (Hermes et al., 2023).

We also advance the methodological toolkit for studying the effects of healthcare supply by exploiting Germany's unique therapist licensing system as a natural experiment. Unlike previous studies that rely solely on market congestion (Costantini, 2025; Prudon, 2025; Williams and Bretteville-Jensen, 2024), our identification strategy provides variation in healthcare supply while holding constant demand, which is achieved by comparing local healthcare markets with the same number of per capita licenses but a different number of providers. We validate our approach using an alternative identification strategy based on market congestion, demonstrating that our results are robust across different empirical designs.

This paper also contributes to the debate whether results from RCTs in developing countries (Baranov et al., 2020; Blattman et al., 2017, 2023; Haushofer et al., 2020; List, 2022; Sevim et al., 2024) are applicable to mental health care systems of high-income countries. We provide evidence that non-price rationing mechanisms, such as provider or patient preferences, may dominate treatment allocation decisions, making supply-side interventions less effective in reaching the highest-need populations than policymakers assume. These results are crucial for the wave of large-scale interventions currently being rolled out in high-income countries aiming to improve access to psychotherapy.[5]

Finally, this paper contributes to the literature on the spatial mobility of patients. Prior research shows that patients are willing to travel to access health care, yet exhibit a strong preference for geographic accessibility (Bauer and Groneberg, 2016; Irlacher et al., 2023; Smith et al., 2018). This paper adds that local market congestion is a key driver for regional mobility in healthcare take-up. We present a spatial analysis showing that locally higher therapy supply increases therapy uptake in neighboring regions, while simultaneously extending waiting times. These patterns suggest that patients first search for treatment close by, and extend their area of search when local options are exhausted. Local supply interventions are thus partly absorbed by demand from surrounding areas. We estimate that 16% of the effect of locally 1 SD higher therapy supply drains into neighboring regions.

2 German Psychotherapy Market

2.1 Patient Access to Mental Health Treatment

In Germany, outpatient psychotherapy is organized on a decentralized matching market. Patients may freely select providers without gatekeeping by a general physician and without any geographic constraints. Treatment is fully covered by statutory insurance, yet patients encounter median waiting times of 139 days between initial contact and the beginning of treatment (Germany Federal Parliament, 2022). This delay also occurs when patients require continuity of care after being discharged from inpatient mental health facilities, as it is

[5]Examples include the IAPT (UK), Better Access Initiative (Australia), Access to Cognitive Behavioural Therapy (Canada), Prompt Mental Health Care (Norway), Mental Health in Primary Care (Netherlands), Project TEACH (New York, USA), CalHope (California, USA), and MCPAP (Massachusetts, USA).

recommended by German medical guidelines (see Appendix A for detailed diagnosis-specific recommendations).

Despite having insurance coverage, some patients opt for paying their psychotherapy out-of-pocket. The two primary reasons for doing so is to reduce waiting times and to avoid official documentation of mental health diagnoses that could affect their employment opportunities or insurance eligibility. Out-of-pocket costs are based on the fee schedule for doctors (GOÄ) and vary between €120 and €190 per session.[6] Out-of-pocket expenditures will be reimbursed by the public health insurance if patients can demonstrate that publicly billed psychotherapy was unavailable. Survey evidence indicates that only 9% of individuals that ever received psychotherapy paid out-of-pocket at least once.(SOEP-IS Group, 2021).[7]

On the supply-side, psychotherapists enjoy discretion over which patients they treat. Among patients that applied for treatment at their practice, providers can choose which patients they want to treat and reject the remaining patients at will, regardless of the patients' medical indication or urgency for treatment.[8]

2.2 Provider Constraints and Market Structure

The psychotherapy market operates under stringent professional entry requirements established by the Psychotherapeutengesetz (Psychotherapists Act). Prospective therapists must first complete a 5-year university degree in either psychology or medicine. Psychology grad-

[6]Short-term therapy can end after 25 sessions. Regular therapy often ends after between 50 and 70 sessions. Yet, longer therapeutic relationships are not uncommon. Thus, the total price of a course of psychotherapy can be anywhere from €3,000 to €13,000 or more.

[7]Health insurance companies evaluate these reimbursement requests on a case-by-case basis. The burden of proof regarding the unavailability of a licensed therapist generally falls on the patient.

[8]If providers observe signs that patients may harm themselves or others they are obligated to inform authorities, but they do not have to provide any emergency care.

uates become psychological therapists, who provide talk therapy exclusively, while medicine graduates become medical therapists, who can additionally prescribe medication and paid sick leave.[9] After finishing their initial degree, candidates must complete a specialized post-graduate apprenticeship combining theoretical instruction with supervised clinical practice. Only after passing the apprenticeship's final examination can individuals practice as psychotherapists in either inpatient or outpatient settings.

Despite these requirements, 44,000 licensed psychotherapists existed in Germany in 2017, with 80% being psychological therapists (Zentralinstitut für die kassenärztliche Versorgung in Deutschland, 2021). More than 70% of these professionals work in outpatient practices (German Statistical Office, 2021), where they face additional market restrictions. Reimbursement rates are administratively fixed through the uniform value scale (Einheitlicher Bewertungsmaßstab) set by the Kassenärztliche Bundesvereinigung (KBV), a commission representing physicians and public health insurers.[10] Licensed therapists (see Section 5.1 for details) receive direct reimbursement from insurers, creating a system in which providers face excess demand but cannot adjust prices to equilibrate the market.

2.3 International Perspective

The German psychotherapy system shares fundamental structural features with the United States that make our findings directly relevant to American policy debates. Both systems operate through decentralized patient-provider matching without centralized allocation, and both face substantial provider shortages under which our documented selection mechanisms

[9]Despite these competences, medical therapists primarily provide talk therapy. The pharmaceutical treatment is administered by outpatient psychiatrists.

[10]The price of therapy is fixed through negotiations between physician and public health insurance representatives, eliminating a role for price as a market-clearing mechanism.

are likely to operate.

Medicare Part B and US Private Insurance. Under Medicare Part B, beneficiaries may, without prior referral or gatekeeping by a primary care physician, directly contract with any therapist who participates in the Medicare program. Like Germany's statutory system, outpatient psychotherapy is mostly covered, and patients select providers from their network. Matching between patients and therapists is fully decentralized: Patients must independently search for providers (that accept Medicare), contact providers, and navigate wait lists.

The parallels extend to provider supply constraints. The KFF, previously known as The Henry J. Kaiser Family Foundation, reports that at the end of 2024, 122 million Americans were living in mental health care professional shortage areas.[11]

Under the Mental Health Parity and Addiction Equity Act, insurers must provide mental health benefits comparable to medical-surgical coverage, but they retain substantial discretion over network composition and reimbursement rates. Less than 20% of non-physician mental health care providers, such as therapists, were in any network Zhu et al. (2017). Such supply-side barriers force patients to conduct extensive searches for providers and often wait extended periods for appointments. As in Germany, therapists operating in this excess-demand environment exercise discretion over which patients to accept, creating conditions favorable to the negative selection we document. Policy makers have recognized this and expanded the number of provider types covered under Medicare Part B. In December 2022, Congress passed the Mental Health Access Improvement Act, which approved mental health

[11] See `https://www.kff.org/other-health/state-indicator/mental-health-care-health-professional-short` (last accessed October 24, 2025).

counselors as providers in Medicare Part B.

Alternative International Models. In contrast, several high-income countries structure access to psychotherapy through gatekeeping systems that can alter the dynamics of selection. In Sweden and Norway, patients generally require primary care referrals before accessing mental health services. In the UK and Canada, while low-level counseling is available via self-referral, more specialized services require a referral. This gatekeeping may reduce negative selection by assigning patients to specialists based on clinical judgment rather than decentralized matching.

3 Data

3.1 Administrative Health Insurance Records

Our analysis is based on daily administrative records from one of Germany's largest statutory health insurance providers. This data set is particularly well-suited for studying mental health care utilization, as Germany's statutory health insurance system covers approximately 90% of the population with standardized benefits across all insurances. Thus, our data are broadly representative of the German population. The comprehensive benefits package includes inpatient and outpatient care, prescription medications, and sick leave compensation.[12]

Our sample consists of all insured individuals aged 18 and above who experienced at least one hospitalization in 2017, for which the primary diagnosis corresponded to ICD-10 codes F01–F99. We designate the 2017 inpatient stay due to mental illness as the index

[12]The health insurance also collects economic information, but this information is only gathered when joining, and even then, it is frequently missing (see Figure B1).

event.[13] Clinical guidelines dictate a combination of pharmaceutical and therapeutic outpatient treatment following a mental health hospitalization. Thus, the design of our sample provides an empirical setting in which all individuals should have received psychotherapy at no personal expenditures. In practice, however, a substantial fraction of individuals did not receive the recommended services. This non-compliance with medical guidelines provides the opportunity to identify non-monetary frictions in the market for outpatient mental health care.

The data spans 2016–2022 and contains daily records of all reimbursed healthcare services. For each healthcare encounter, we observe (i) ICD-10 diagnosis codes, (ii) treatment costs and duration, and (iii) unique provider identifiers for hospitals, outpatient facilities, and individual physicians. We aggregate these spell-level data to construct a quarterly panel of healthcare utilization relative to the quarter of index hospitalization.

We augment the individual-level data with two additional sources. First, the insurance provided us with a register of licensed psychotherapists, which we linked to patient records to examine provider accessibility. Second, we incorporate county-level economic indicators from the Federal Statistical Office, including GDP per capita, population density, and aggregate mental health hospitalization rates across all insurance providers. To capture broader regional amenities that can influence mental health and healthcare-seeking behavior, we use an established county-level index that measures demographic and socioeconomic attractiveness.[14]

[13]Hospitals must classify all inpatient stays as emergencies or scheduled events. However, there is no unified definition of emergency cases, and hospitals can decide on their own. In our sample, approximately half of the index stays are coded as emergency.

[14]The strength index ranks German counties based on their demographic structure (e.g., the fertility rate and population age structure), socio-economic factors (e.g., the crime rate and public debt), their labor

3.2 Sample Construction

We begin with administrative records for approximately 77,000 individuals with any psychiatric hospitalization history in our insurance dataset. To construct our analysis sample, we apply the following restrictions. First, we require that individuals have experienced a psychiatric hospitalization in 2017 (the index event) for which valid geographic identifiers are available. Second, we drop individuals who switched insurance providers before 2021 to ensure that our follow-up data are complete. Third, we omit people aged 70 or older. Finally, we restrict the sample to individuals, that were initially hospitalized due to mood disorders (F30–F39), anxiety disorders (F40–F49), behavioral disorders (F50–F59), and personality disorders (F60–F69).[15] From the analysis sample, we also exclude patients who were already receiving psychotherapy at the time of their index hospitalization to cleanly identify treatment initiation.

The remaining sample contains 38,264 individuals. Table 1 Column 1 summarizes their baseline characteristics. Mood disorders, primarily major depression, account for the majority of index hospitalizations. The length-of-stay distribution exhibits substantial right skew, with the median stay duration being 30 days. Despite the fact that clinical guidelines recommend psychotherapy for these conditions, the uptake of treatment remains modest. Only 26% initiate therapy within one year after discharge, and only 12% do so within 90 days. At the same time, 46% of patients are readmitted to the hospital due to mental illness within three years after their index discharge.

market (e.g., the job density and workers' education), and their innovativeness (e.g., the number of patents and workers in R&D). See (Prognos AG, 2016) for details.

[15]These restrictions reflect clinical guidelines indicating that psychotherapy has limited effectiveness for disorders with primarily physiological etiology or severe cognitive impairment.

3.3 Key Variables

This section provides an overview of the variables that are important for the analysis.

Outpatient mental health treatment We define that individuals receive psychotherapy in a quarter if there is at minimum a two-day therapy spell.[16] Moreover, we consider that individuals received therapy following up on their index hospitalization if they initiated psychotherapy within one year after discharge. Accordingly, we consider individuals receiving guideline-consistent mental health treatment in a quarter if they receive therapy and filed a prescription for psychotropic drugs in the reference or the prior quarter.

Case severity To proxy case severity, we predict individuals' risk of readmission in the absence of guideline-consistent health care. For that, we regress an indicator of whether individuals are readmitted within three years after index discharge on demographic characteristics, 2-digit main and side diagnoses, and healthcare uptake in 2016 using ten-fold cross-validated logistic regression. We fit the model only using individuals not receiving psychotherapy following their index discharge. In doing so, we predict the risk of readmission in the absence of follow-up psychotherapy.[17]

Demand for health To measure individuals' effort to achieve better health, we identify the uptake of preventive health care measures that are fully covered by health insurance. In particular, we identify whether individuals received any vaccinations, preventive health checks, or preventive screenings for certain types of cancer in the year before their index hospitalization.[18]

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[16]Single-day therapy spells may reflect initial assessments that did not result in long-term therapeutic treatment.

[17]To confirm the quality of the predictions, Figure B2 shows the association of the predicted readmission risk with the true in-sample readmission rates.

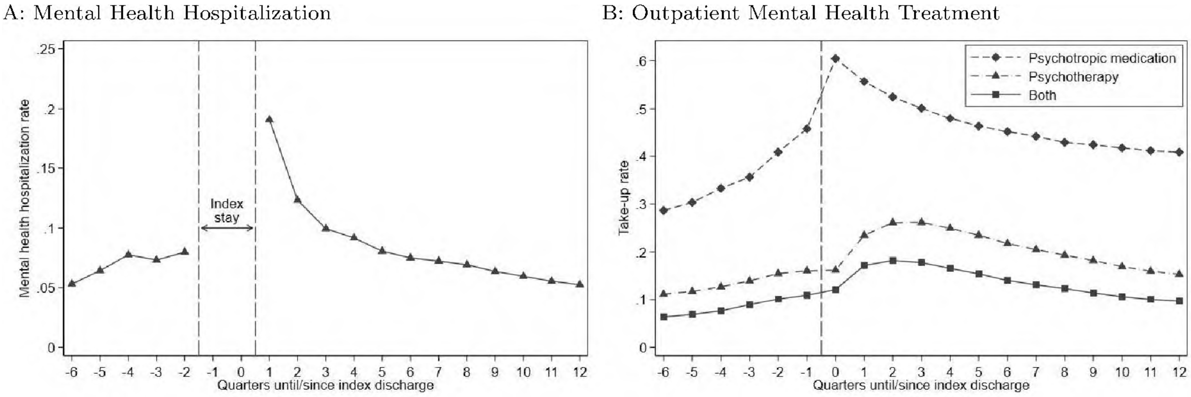
[18]We exclude vaccinations that are only recommended for traveling. We consider screenings for skin, colon,

4 Healthcare Take-up after Hospital Discharge

4.1 Mental Health Treatment and Relapse Rates

Panel A of Figure 1 shows the quarterly rates of mental health hospitalizations by time until individuals were discharged from the inpatient stay, leading to their inclusion in the sample. After index discharge, individuals' quarterly relapse rates are high. In the first quarter after discharge, 20% of the individuals are readmitted. Over time, the readmission rate converges back towards a baseline level of 5%. Panel B shows the outpatient mental health care utilized during the same period. Based on medical guidelines, the recommended treatment for the present diagnoses is a combination of talk therapy and psycho-medication. Although both the take-up of therapy and psychotropic drugs increase sharply after index discharge, only 15% of patients receive treatment in line with medical guidelines. This treatment gap is driven by low therapy initiation, despite therapy being fully covered by German health insurance.

Figure 1. Readmission Rates and Treatment Uptake by Quarter Since Discharge



Notes: The figure shows average mental health care take-up rates by quarter since index discharge (quarter 0). The sample includes individuals receiving therapy during their index hospitalization. See B3 for a replica that excludes those receiving therapy during their index hospitalization.

breast, and prostate cancer.

4.2 Selection into Therapy

Among patients discharged from mental health hospitalization, those receiving psychotherapy as follow-up care are a highly selective sample. Columns 2 and 3 of Table 1 show the average characteristics of individuals with and without follow-up therapy after their index discharge. Patients receiving follow-up therapy are more likely to be women and diagnosed with a mood disorder.

In addition, Table 1 provides descriptive evidence for the selection of milder cases into therapy. First, individuals who receive follow-up therapy have a lower chance of previous mental health hospitalizations. Second, in absence of the treatment effect of therapy, the recipients' risk of readmission within three years is significantly lower, which is driven by the right tail of the readmission-risk distribution (see Figure B4). To further investigate, Figure 2 visualizes patients' therapy uptake (Panel A) and waiting times (Panel B) across deciles of readmission risk. A 10 pp higher readmission risk corresponds to a 3.5 pp higher chance of initiating therapy following the index hospitalization and a 7.5 days longer waiting time. Since the predictions are based only on individuals' predetermined medical histories, this correlation does not reflect reversed causation, hence the urgent need for hospitalization hindering individuals in seeking outpatient therapy. Thus, demographic and medical factors predictive of hospital readmission are strongly related to non-compliance with medical guidelines.

The selection of patients with a lower readmission risk into treatment may operate through both demand- and supply-side channels. On the demand side, accessing therapy requires substantial non-monetary costs, such as search effort, waiting periods, and potential rejections, that may exceed the capacity of individuals with severe mental health conditions. In line, Table 1 shows that recipients of therapy are considerably more likely to have invested in their health through preventive care.

On the supply side, the German reimbursement system for outpatient psychotherapy creates incentives for providers to disproportionately treat less severely ill patients. Because reimbursement rates are fixed per session and therapists can freely select and dismiss patients, providers can screen for patients whose treatment requires relatively low effort. Kugelmass (2016), for example, shows that German therapists prefer patients of higher socioeconomic status. Consistently, Figure 3 descriptively shows that among patients receiving therapy eventually, the timing of therapy initiation aligns with individuals' mental health hospitalization rate returning to baseline levels. While the decline in readmission rates may partly reflect therapeutic success, its magnitude appears to exceed effect sizes documented in prior research.[19] Instead, the pattern of Figure 3 may reflect that psychotherapists admit some patients only once they have recovered sufficiently from the initial mental health shock that triggered their index hospitalization.

[19] Serena (2025) finds that psychotherapy reduces mental health hospitalizations by approximately 5 percentage points among 37-year-olds in Denmark.

Table 1. Sample Characteristics

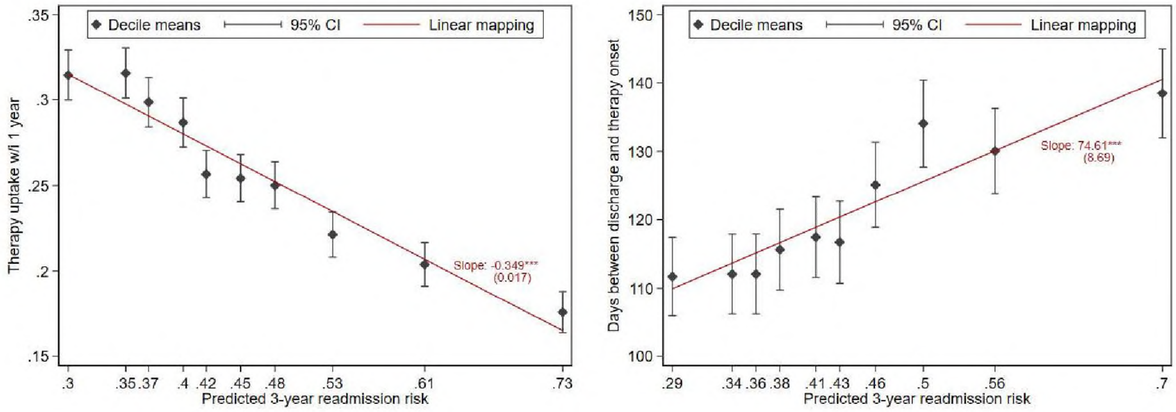
	Full sample	Therapy w/i 1 year		
		Yes	No	t-stat Δ
	(1)	(2)	(3)	(4)
Age at discharge	39.78 (14.92)	40.00	39.71	1.75
Female	0.60 (0.49)	0.68	0.57	19.83
3-year readmission risk	0.46 (0.13)	0.44	0.47	-20.77
Health Care in 2016				
MH hospitalization	0.15 (0.36)	0.12	0.16	-11.78
Psychomedication	0.60 (0.49)	0.60	0.60	-0.27
Preventive healthcare	0.45 (0.50)	0.53	0.42	17.62
Index Hospitalization				
Days of index stay	41.12 (32.02)	47.20	38.99	22.18
ICD-F3: Mood disorder	0.68 (0.47)	0.72	0.67	8.62
ICD-F4: Anxiety disorder	0.21 (0.41)	0.20	0.22	-3.41
ICD-F5: Behavioral disorder	0.03 (0.18)	0.04	0.03	2.07
ICD-F6: Personality disorder	0.07 (0.25)	0.04	0.08	-13.08
Therapy Uptake				
W/i 90 days after discharge	0.12 (0.33)			
W/i 365 days after discharge	0.26 (0.44)			
Ever after discharge	0.38 (0.49)			
N	38,264	9,858	28,361	

Notes: The table contains means and standard deviations (in parentheses). Column 1 contains the full analysis sample after exclusions, Column 2–3 Individuals initiating/ not initiating psychotherapy within one year post-discharge, and Column 4 t-statistic for testing equality between Columns (2) and (3)

Figure 2. Therapy Take-up and Case Severity

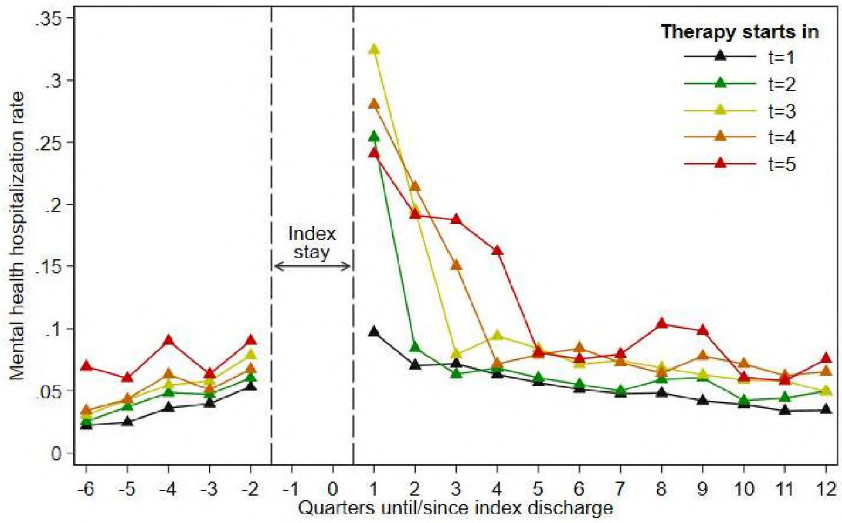
A: Extensive margin: uptake within one year

B: Intensive margin: waiting times



Notes: Panel A depicts the share of individuals initiating therapy within one year after discharge from their index hospitalization across deciles of the predicted three-year readmission risk. The horizontal axis denotes the average readmission risk per decile. For the subset of individuals starting therapy within one year, Panel B shows the average waiting times (as the days between discharge and therapy onset) across deciles of readmission risk. The red lines depict linear fits. The parentheses contain standard errors clustered at the individual level. The whiskers denote 95% CI.

Figure 3. Quarterly Mental Health Hospitalization Rates by Timing of Therapy



Notes: The figure shows quarterly mental health hospitalization rates for individuals initiating therapy at different points in time relative to their index hospital discharge. Index discharge occurs in period 0.

5 The Effects of Higher Therapy Supply

5.1 Identifying Variation

To identify the effects of a higher supply of outpatient psychotherapy in a setting in which patients with lower case severity select into therapy, we employ two complementary strategies to measure the local supply of therapy.

For our primary measure, we exploit quasi-random variation in psychotherapy supply generated by Germany's therapist licensing system. Market entry is regulated by the KBV through a fixed allocation of county-specific licenses, which outpatient therapists require to bill the public health insurance. For license allocation, Germany's 400 counties are assigned to one of six demand-type categories based on historical patterns of health care utilization and cross-county patient flows. The maps of Figure 4 show these demand types. Counties with higher expected demand, such as densely populated urban areas, are allocated more licenses per capita to match the higher prevalence of mental illness. Because the number of licenses within each county is fixed, prospective outpatient therapists must purchase a license from an incumbent provider. License prices are determined at market conditions and capitalize local amenities and demand conditions. Accordingly, prices varying widely across counties from less than €10,000 to more than €100,000.[20]

The licensing system is intended to equalize outpatient mental health care supply across regions with comparable demand. In practice, however, the number of therapists per capita varies substantially among counties with the same number of licenses per capita. The primary reason arises from the option for two therapists to share one license. Under a shared license,

[20]For comparison, in the year 2023, the median revenue per practice for psychotherapy was €81,000. There can be multiple providers per practice (German Statistical Office, 2023).

billable therapy hours are capped at 25 per week and practitioner. Therapists in such arrangements work an average of 29.1 total weekly hours, compared with 39.8 hours for full license holders (Bundes Psychotherapeuten Kammer, 2023). Thus, per-license labor supply is approximately 50% higher if the license is shared.[21]

This large difference in labor supply per license creates variation in treatment availability irrespective of demand, which we utilize for identification. Because statutory health insurance providers do not observe whether a therapist operates under a shared or a full license, we approximate the prevalence of license sharing by counting the number of outpatient therapists per capita and county. Within each demand-type category, we compute the z-standardized deviation of therapist density from the type's mean. To purge mechanical sources of variation in the number of therapists, we residualize this measure with respect to an age-adjustment factor and five-year population growth.[22] In our preferred specification, we censor the tails of the measure at the 5 and 95 percentiles to avoid outlier bias. Henceforth, we refer to the measure of local therapy supply based on the license sharing as *excess supply*.

The supply variation induced by license sharing in 2017 is visualized by the coloring in Figure 4. In the dark gray areas, excess supply exceeds the demand-type median, and in the light gray areas, it lies below the median.[23] The spatial correlation of a county's excess

[21]The license-sharing became popular among providers throughout the 2010s. In 2017, 44% of all licenses are shared, compared to 9% in 2010 (see Figure B5).

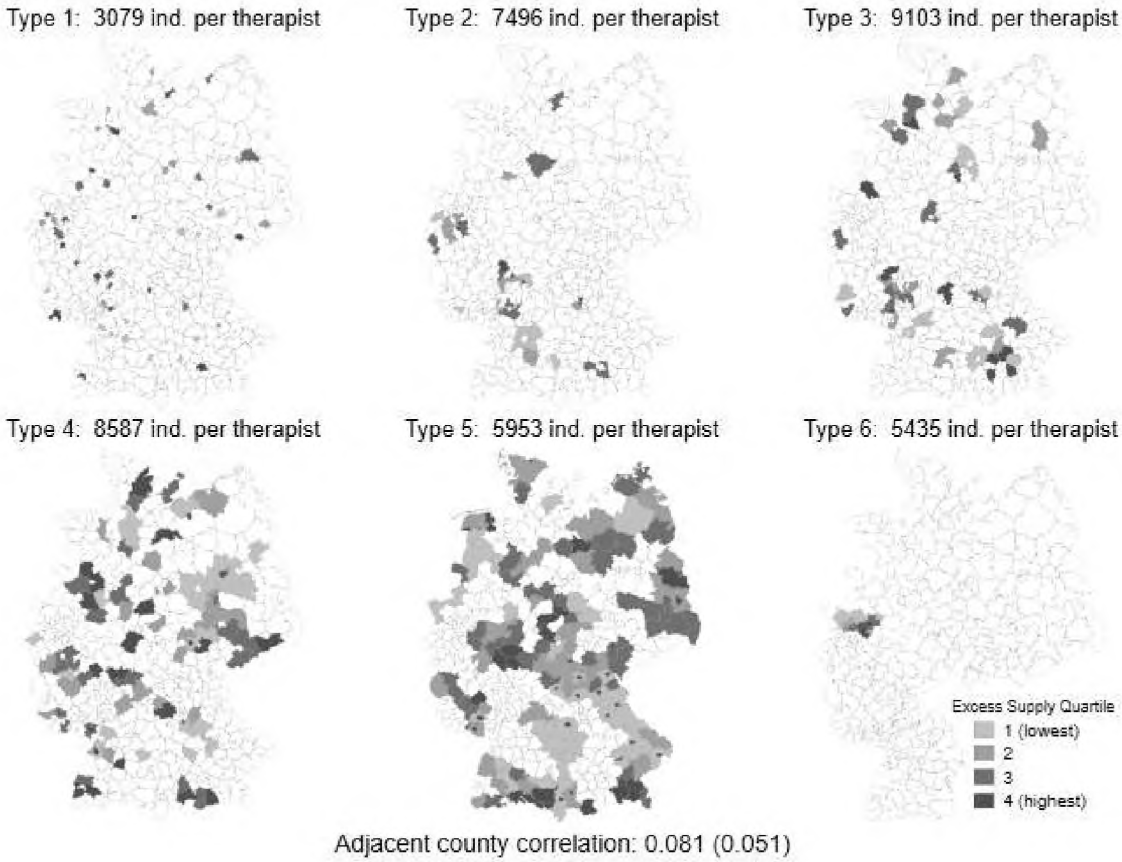
[22]First, the KBV adjusts its license allocations based on age composition, granting additional licenses to counties with above-average shares of younger people, who exhibit higher demand for mental health care. Second, the system responds slowly to population changes. In case of population decline, once the density of the therapist exceeds 140% of the target ratio, the licenses can be revoked, but this rarely happens. Instead, no new licenses are issued as the incumbent therapists retire.

[23]For comparison, Figure B7 shows the spatial distribution of all patients and all therapy recipients in our sample.

supply with the supply in its adjacent neighbors is statistically insignificant. Table 2 contains the results of regressing the number of therapists per county on excess supply within the six demand types. A 1 SD higher excess supply translates into 40 (0.2) additional providers (per 1000 inhabitants), or 20 additional full-time equivalents when considering that two shared-license holders provide only 1.5 times the labor supply of a single full-license holder.

Second, we follow the approach of the recent literature and measure local availability of psychotherapy using a leave-one-out design. The authors argue that healthcare uptake of individuals in the same region (Prudon, 2025; Williams and Bretteville-Jensen, 2024) or from the same hospital captures (Costantini, 2025) local congestion of the healthcare market. For each individual, we thereby compute the share of other patients residing in the same county who received follow-up therapy within one year. We omit the seven out of the 400 counties with fewer than 10 individuals in our sample. To align interpretation, we z-standardize the measure, analogously. Henceforth, we refer to the supply measure based on the leave-one-out approach as *local congestion*. Figure B8 shows the spatial variation of the local congestion, and Figure B9 shows the correlation of both supply measures. A 1 SD higher excess supply is associated with a 0.4 SD higher local congestion.

Figure 4. Variation in Therapy Supply Within Demand Planning Types



Notes: The maps visualize the excess supply of psychotherapy within each demand type in quartiles. The darker (lighter) counties oversupply (under-supply) psychotherapy, with demand for therapy held constant. The header of each map shows the relation between a demand type's population and the allocated licenses. The bottom contains the results of regressing a county's excess therapy supply on the average excess supply of its adjacent neighbors ($N = 400$). The parentheses contain standard errors clustered at the county level.

Table 2. Correlation of Therapy Supply and the Number of Therapists per County

	Number of therapists		Therapists / tsd capita	
	(1)	(2)	(3)	(4)
Excess supply	40.31***		0.19***	
	(11.25)		(0.01)	
Congestion		15.21**		0.06***
		(7.44)		(0.01)
Observations	400	393	400	393
Outcome Mean	117.7	117.7	0.46	0.46
Demand Type FE	Yes	Yes	Yes	Yes

Notes: The table contains the results of regressing a county's total number of therapists (Columns 1&2) or the number of therapists per 1000 inhabitants (Columns 3&4) on a measure of therapy supply. All regressions include demand type fixed effects. The standard errors in parentheses are clustered at the county level. The asterisks indicate the significance levels: * < .10, ** < .05, *** < .01

5.2 Estimation

To identify the effects of higher therapy availability on take-up, we compare patients who were simultaneously hospitalized and discharged into outpatient healthcare markets with the same demand for therapy, yet a different supply. By focusing on individuals with a recent mental-health hospitalization, we ensure that all patients in the sample are clinically recommended for therapy. In practice, we estimate a generalized difference-in-difference model using the following baseline regression:

$$y_{it} = \alpha_i + \vartheta_{td} + \sum_{\tau \neq -2} \beta_\tau \, 1[t = \tau] \, z_c + \varepsilon_{it} \quad (1)$$

y_{it} denotes the use of healthcare consumption by individual i at quarter t re-centered to the quarter the individual was discharged from its index mental health hospitalization. The unit fixed effects α_i capture time-invariant variation in healthcare uptake within individuals. ϑ_{td} denotes time-by-demand type fixed effects, which, for each demand type, absorb a general trend in health-care uptake around individuals' mental health hospitalization irrespective of therapy supply. Their inclusion ensures that the identifying variation stems from comparing individuals who were discharged into healthcare markets with the same demand for therapy. Finally, the model contains an interaction of time fixed effects and the standardized measure of therapy supply $z_c \in \{Excess\, Supply_c,\, Local\, Congestion_c\}$ in the county c. The adjacent coefficients β_τ capture the dynamic effects of facing different supply-induced availability of therapy following a mental hospital discharge. For $\tau \geq 0$, β_τ measures the effects of a 1 SD higher therapy supply on individuals' follow-up treatment after hospital discharge, while $\tau < 0$ unveils whether capacity at discharge determines past healthcare uptake. Quarter -2 serves as the reference period.

To estimate the effects of higher therapy supply statically, we collapse eq. (1) into a two-period model. $y_{i\theta}$ thereby denotes individuals' healthcare take up in the year $\theta \in \{pre,\, post\}$ before or after their index hospital discharge.

$$y_{i\theta} = \alpha_i + \vartheta_{d\theta} + \beta\, 1[\theta \in \{post\}]\, z_c + \varepsilon_{i\theta} \tag{2}$$

The new coefficient of interest, β, captures the effect of being discharged into a healthcare market with a 1 SD higher therapy supply on treatment uptake within one year after index hospital discharge. We estimate both equations using OLS. For inference, we cluster the standard errors at the county level following Abadie et al. (2022).

5.3 Validity

Consistent estimation of β builds on the generalized parallel trends assumption that, in absence of license sharing, individuals in high and low excess supply regions remain on the same health-care trajectories around their index hospitalization. Under this interpretation, our estimation would produce biased results if, despite constant demand, factors determining the prevalence of license sharing also distort patients' uptake of outpatient care following a mental health hospitalization.

One threat to our identification would be that providers altruistically prefer shared licenses to counteract local shortages of therapy supply. A practitioner's choice to obtain a shared over a full license is, however, largely motivated by economic factors. First, buying a shared license is considerably cheaper. While there are no official records on selling prices, shared licenses may cost up to 50% less. This potential discount is important given that aspiring psychotherapists are severely budget-constrained after finishing their education, and the price for a full license may exceed €100,000.[24] Second, buying a shared license may reflect preferences for part-time work. To ensure a stable health-care supply, holders of a full license are legally required to provide 25 hours of therapy per week. Under a shared license, this number is reduced by half. Thus, providers have strong incentives to base their licensing choice on economic rather than public health motives.

To test whether the prevalence of license sharing is associated with patient characteristics, Table 3 contains t-statistics of regressing local therapy supply on patient characteristics. Neither patients' case severity nor their past mental healthcare take-up is correlated with

[24] Working as a psychotherapist in Germany requires a 5-year university degree followed by 3 years of vocational training. Tuition for the university degree is small (€300–500 per semester), but for the vocational training, tuition amounts up to €20,000.

therapy supply. However, on the regional level, prevalent license sharing is correlated with a higher supply of non-therapeutic outpatient mental health care providers, that is, outpatient psychiatrists. We perform several exercises to ensure that this correlation does not confound our results.

First, by including unit fixed effects we hold constant any time-invariant variation in healthcare uptake arising from county characteristics. Second, we show that excess supply is not predictive of individuals' take-up of non-therapeutic outpatient mental health care and physical health care, either before or after the index hospitalization (see Figure 5). In addition, excess supply is also not predictive of individuals' past uptake of psychotherapy. Then, we confirm that our estimates of β are insensitive to controlling for all, or a subset of the observed county characteristics. Last, we replicate our findings using local congestion as a measure of therapy availability, which is not correlated with regional covariates (see Column 4 of Table 3).

Table 3. Correlation of Therapy Supply and Individual and Regional Covariates

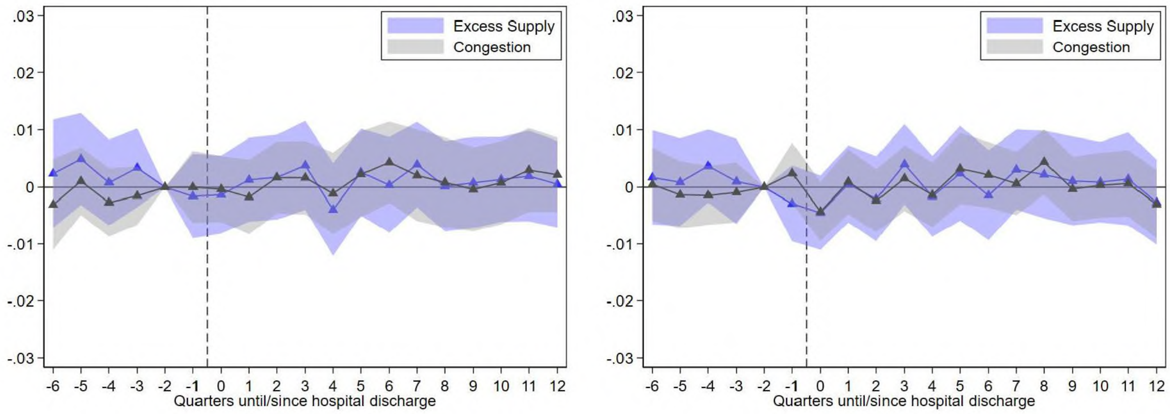
	T-statistic			
	Excess Supply		Congestion	
	(1)	(2)	(3)	(4)
Panel A: Individual characteristics				
Age at discharge	-0.86	-1.05	0.12	0.08
Female	-2.80	-2.91	-1.29	-1.03
Days of index stay	-0.77	-0.43	-0.32	0.09
Index diagnosis: ICD-F3	1.95	1.75	0.53	0.35
Index diagnosis: ICD-F4	0.75	0.65	0.12	0.23
Index diagnosis: ICD-F5	0.87	0.73	-0.26	-0.19
MH hospitalization in 2016	0.96	0.18	-0.05	-0.18
Psychomedication in 2016	0.50	0.07	-0.07	-0.18
3-year readmission risk	-0.41	0.68	-0.36	-0.30
Panel B: County characteristics				
Population	-1.49	-1.91	-2.53	-1.67
Population density	0.79	3.09	2.97	1.65
GDP per capita	-1.96	-0.72	-0.60	-0.56
Unemployment rate	0.52	2.13	-1.98	-2.29
Amenity index	-0.74	-1.44	-0.92	-0.93
General practitioners per capita	2.22	2.59	0.95	1.25
Non-therapeutic MH-care providers per capita	2.55	4.58	-1.14	-1.07
Observations	38,219	38,219	38,219	38,219
Demand Type FE	No	Yes	No	Yes

Notes: The table shows t-statistics of regressing excess therapy supply and local congestion on individual and regional covariates. The standard errors are clustered at the county level.

Figure 5. Dynamic Placebo Effects of a 1 SD Higher Therapy Supply on Healthcare Usage

A: Outpatient visit with a non-therapeutic provider

B: Outpatient visit due to a pulmonary disease



Notes: The figure shows quarterly estimates of higher therapy supply on the quarterly uptake of outpatient care using eq. (1). The binary outcomes are denoted by the sub-headers and the measure for therapy supply by the coloring of the 95%-level CI. The regressions further include county-level controls (see Table 3) interacted with time fixed effects. The standard errors are clustered at the county level.

5.4 Results on Therapy Take Up

Figure 6 provides effect estimates of higher therapy supply on therapy uptake and medical guideline compliance following a mental health hospitalization. The markers denote quarterly estimates according to eq. (1) and the top right contains static estimates based on eq. (2). The results provided are local effects on compliers and hence on individuals whose take-up of therapy is supply-sensitive. A 1 SD higher excess therapy supply increases the share of individuals receiving follow-up psychotherapy by $2-2.6$ pp, which resembles a 10% increase from the sample mean. The share of individuals receiving guideline-consistent treatment (i.e., a combination of talk therapy and psychotropic medication) increases by a similar margin. These results imply that, in the counterfactual, supply-sensitive individuals, who would not initiate psychotherapy in absence of higher supply, would receive psychotropic medication, nonetheless. Consequently, higher therapy supply does not crowd out pharmaceutical treatment; instead, psychotherapy and medication appear to be complementary treatment options.

The dynamic patterns in Figure 6 indicate that additional therapy supply does not raise psychotherapy uptake immediately after discharge from mental health hospitalization, but instead with a delay of one to two quarters. This lag suggests that individuals receiving therapy due to a marginally higher supply still face binding capacity constraints and must queue for treatment, which takes a median of 99 days among patients seeking therapy after mental health hospitalization.[25] Using local congestion as an alternative measure for therapy availability produces quantitatively similar estimates (see Figure C1).

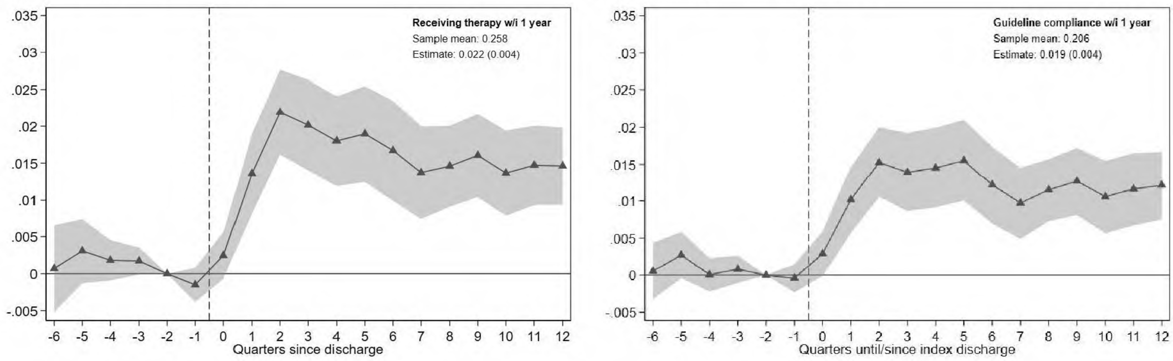
The large effects of therapy supply on therapy uptake among patients with severe mental conditions arise in an institutional setting in which outpatient providers can freely select their patients. Additional capacity generated by license sharing can therefore be allocated at providers' discretion, with no explicit prioritization by clinical severity. Our findings thus indicate that a nontrivial share of the marginal supply is absorbed by individuals seeking follow-up psychotherapy after an inpatient stay, a group for whom treatment is explicitly recommended by clinical guidelines. Taken together, these results show that capacity constraints partly explain the puzzle of low compliance with medical guidelines among individuals with severely ill mental health.[26]

[25] Figure B10 shows the density of waiting times among patients receiving therapy within one year after index hospital discharge.

[26] Figure B11 shows heterogeneous effects for various sub-samples based on demographic and medical covariates at baseline. The effects of higher therapy supply thereby remain homogeneous when omitting individuals with a previous mental health hospitalization in 2016 or when restricting the sample to patients diagnosed with mood disorders only.

Figure 6. The Effects of a 1 SD Higher Therapy Supply on Therapy Take-Up

A: Receiving psychotherapy B: Medical guideline compliance



Notes: The figure shows estimates of higher excess therapy supply. In Panel A (B), the outcome is an indicator of whether individuals received any psychotherapy (in combination with psychotropic medication) in a given period. The markers depict quarterly estimates produced using eq. (1). The estimation further includes county-level controls (see Table 3) interacted with time fixed effects. The shaded area shows 95%-level CI. The standard errors are clustered at the county level. The top right corner contains static DiD estimates comparing the health care take-up in the year before and after index discharge using eq. (2). The parentheses contain standard errors clustered at the county level.

5.5 Intensive Margin Results on Treatment Quality

Beyond take-up, additional therapy supply may also affect the quality of treatment on the intensive margin. To investigate, we restrict the sample to individuals initiating psychotherapy within one year after their index hospital discharge. Using these therapy recipients, we regress several dimensions of treatment quality on local therapy supply and demand type fixed effects. Since this specification does not allow for individual fixed effects, we instead add the individual- and county-level baseline covariates listed in Table 3 to the regression. Table 4 summarizes the results. On the intensive margin, a 1 SD higher therapy supply reduces waiting times by almost 4 days. While the shorter treatment delay is significant in statistical terms, its economic magnitude is small compared to the sample mean of 122 days. In addition, therapy sessions become marginally more frequent. As a result, the total number of therapy sessions within one year after index discharge increases.[27]

To assess whether higher therapy supply reduces the search effort required to obtain psychotherapy, Column (5) of Table 4 examines effects on patients' commuting behavior. A 1 SD higher therapy supply significantly raises the probability that individuals find treatment in their county of residence. This pattern indicates that greater supply alleviates search and travel costs that may otherwise impede access to care, particularly for immobile patients, such as patients with more severe conditions or binding budget constrains.

Put together, these findings contradict the sampling choices of recent economic research (Prudon, 2025; Costantini, 2025; Williams and Bretteville-Jensen, 2024), that investigates the effects of mental health care availability exclusively among individuals receiving treatment eventually. The authors thereby impose the assumption that their measure for mental health care supply only affects individuals' health and labor supply through reduced waiting time. The results of this paper, in contrast, emphasize that increased treatment availability strongly affects its uptake. Thus, whenever treatment availability is high and waiting times are marginally shorter, the stock of individuals receiving treatment expands substantially.

[27] Another angle through which therapy supply may affect treatment quality is the match quality between patients and providers. Higher supply may allow patients to switch providers more easily if they are dissatisfied with the treatment. However, only a tiny fraction of individuals receive therapy from multiple providers in the year after their index discharge (see Column 4 of Table 4).

Table 4. Intensive Margin Effects of a 1 SD Higher Therapy Supply on Therapy Quality in the Year After Discharge

	Waiting times	Number of sessions	Days between sessions	Unique therapists	Therapy in county of residence
	(1)	(2)	(3)	(4)	(5)
Excess supply	-3.68***	0.58***	-0.22***	0.00	0.05***
	(1.22)	(0.15)	(0.08)	(0.00)	(0.01)
Observations	9,774	9,774	9,575	9,774	9,302
Outcome mean	122.2	16.99	12.57	1.02	0.63
Demand type FE	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes
Regional controls	Yes	Yes	Yes	Yes	Yes

Notes: The table shows intensive margin effects of higher excess therapy supply on therapy recipients. They are produced by regressing a static post-discharge outcome on excess therapy supply, demand type fixed effects, and the covariates listed in Table 3. The sample consists of individuals initiating therapy within one year after hospital discharge. The outcomes are the number of days between index hospital discharge and therapy onset (Column 1), the number of therapy sessions within one year after discharge (Column 2), the average days between the therapy sessions (Column 3), the number of practitioners individuals started a therapy with (Column 4), and an indicator whether individuals initiated therapy in their county of residence (Column 5). In Column 3, the sample excludes individuals with a single therapy session within one year after discharge. The standard errors in parentheses are clustered at the county level. The asterisks indicate the significance levels: * < .10, ** < .05, *** < .01

5.6 Robustness and Sensitivity

This section summarizes the results of several tests on the sensitivity and robustness of the results outlined in the previous section. All Figures can be found in Appendix C. First, we investigate how the inclusion of time-invariant covariates at the county level changes the estimates. Since the unit fixed effects capture any time-invariant variation, we interact these covariates with time fixed effects. Figure C2 provides dynamic estimates when including none and all county covariates listed in Table 3. In addition, the Figure shows the distribution of estimates produced when including every possible combination in between. Including covariates changes the point estimates only marginally and leaves their qualitative interpretation unchanged.

Next, we address the concern that individuals may manipulate the length of their index hospital stay in response to the availability of outpatient follow-up treatment. For that, we replicate our results using the quarters since index hospital admission as the unit of time (see Figure C3). This exercise produces analogous results, which is unsurprising, because the length of the index hospitalization is uncorrelated with local therapy supply (see Table 3).

Then, we re-specify the coding for our measures of local therapy supply. Instead of using a continuous measure, Figure C4 shows the results for comparing regions with above- and below-median therapy supply in a binary design. Increasing the average difference in therapy supply between these groups (i.e., by comparing the top to the bottom supply quintile instead of performing a median split) results in larger point estimates, reflecting the increased difference in supply.

Last, we address excessively high and low values of therapy supply in some counties. Particularly in the federal state of Hesse and in small yet densely populated counties, high values of excess supply are over-represented (see Figures C6 and C7). Since estimating the effects of a continuous measure of therapy supply may be sensitive to these outlier values, we censor therapy supply at the 5th and 95th percentiles in our main specification.[28] Omitting the outlier counties instead does not largely affect the estimates (see Panel A of Figure C8). Similarly, the results are insensitive to omitting the entire state of Hesse, or any other federal state, from the estimation (see Figure C9). As a third option, we coarsen therapy supply into deciles and estimate the effect of a 1 decile higher therapy supply (see Figure C8, Panel B).

5.7 Regional Spillovers

Although psychotherapy supply is regulated at the county level, individuals face no legal restrictions on where they seek treatment. In our data, 33% of individuals receiving therapy after their index discharge do so outside their county of residence. The results presented in Column 5 of Table 4 thereby suggest that local supply shortages contribute to the substantial spatial mobility in treatment take-up. Accordingly, local increases in supply may raise therapy utilization not only within the county itself but also in its neighboring areas; first, by reducing competition for treatment within these surrounding areas, and second, by improving the options of individuals in the surrounding areas to commute towards the higher supply themselves.

To quantify regional spillovers of locally higher therapy supply, we identify, for each

[28] Figure C5 shows the raw correlation of excess supply and therapy uptake within one year after hospital discharge.

county, all adjacent counties. On average, each county has five adjacent neighbors. Then, we re-estimate eq. (1), replacing the county's own therapy supply with the average therapy supply of its adjacent neighbors. The results are shown in Figure 7. A 1 SD higher supply among the adjacent counties significantly increases therapy uptake by 1.6 pp. The dynamic response indicates that these spillover effects peak approximately one quarter after the corresponding effects of locally higher supply (see Figure 6). This timing pattern suggests that individuals initially search for psychotherapy within their county of residence and expand their search radius only after failing to secure local treatment.

To estimate what proportion of the effect of a locally 1 SD higher therapy supply remains in its county of origin and what share drains into surrounding areas, we employ a gravity-style estimation approach. For that, we establish a county-level data set of all adjacent county pairs ($N = 2,044$). In the adjacent county pair (a, b), let $\bar{y}_{a(ab)}$ denote the average psychotherapy take-up among residents of county a within one year after mental hospital discharge, and $\bar{y}_{b(ab)}$ the corresponding average in county b. Then, we regress both averages on therapy supply in county a:

$$\bar{y}_{a(ab)} = \beta^a \, z_a + X_a + X_b + \varepsilon_{a(ab)} \tag{3}$$

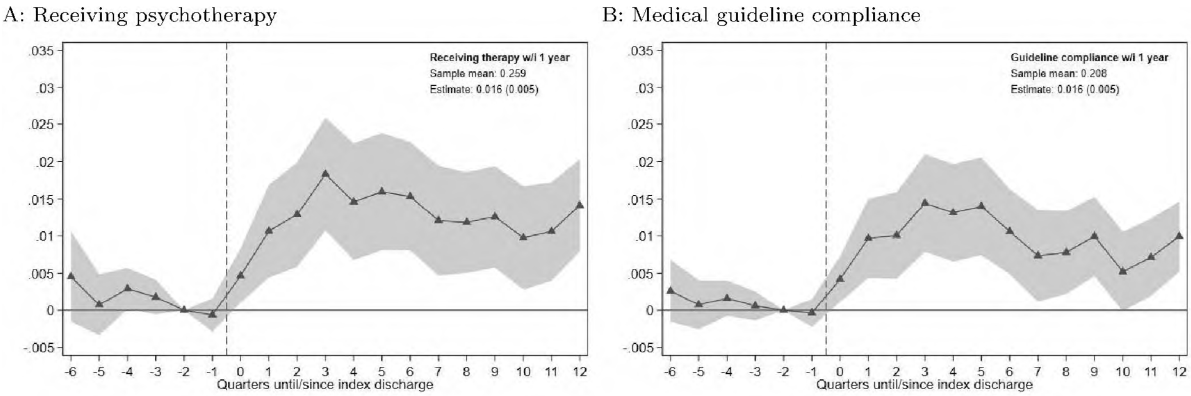
$$\bar{y}_{b(ab)} = \beta^a \, z_a + X_a + X_b + \varepsilon_{b(ab)} \tag{4}$$

Depending on the equation, the coefficient β^a denotes the effect of a 1 SD higher therapy supply in county a on its own therapy take-up (eq. 3) and on the therapy take-up in the adjacent counties (eq. 4). The total effect of higher therapy supply is thus given by

$\beta^a_{eq(3)} + \beta^a_{eq(4)}$.[29] The regressions additionally include the regional control variables listed in Table 3 for both counties of the pair, as well as the therapy supply of the adjacent county b.

Table 5 summarizes the results. A 1 SD higher therapy supply increases therapy take-up in the year after index hospital discharge by 2.3 pp percent locally and by 0.4 pp in the adjacent counties. Thus, a 1 SD higher supply results in a total effect size of 2.7 pp, from which 84% remains in the local county and 16% drains into adjacent counties. This degree of regional spillover matches the results of Figure 7, where a 1 SD higher supply throughout the (on average) five adjacent counties produces an effect estimate that is approximately $5 \times 16\% = 80\%$ the size of the effect estimate of a locally 1 SD higher supply.

Figure 7. The Effects of a 1 SD Higher Therapy Supply in Adjacent Counties on Therapy Take-Up



Notes: The figure shows estimates of higher excess therapy supply in adjacent counties. Local excess supply in eq. (1) and (2) is thereby replaced by the average excess supply of directly adjacent counties. On average, a county has five adjacent counties. In Panel A (B), the outcome is an indicator of whether individuals received any psychotherapy (in combination with psychotropic medication) in a given period. The markers depict quarterly estimates produced using eq. (1). The regressions further include county-level controls (see Table 3) interacted with time fixed effects. The shaded area shows 95%-level CI. The standard errors are clustered at the county level. The top right contains static DiD estimates comparing the health care take-up in the year before and after index discharge using eq. (2). The parentheses contain standard errors clustered at the county level.

[29] Note that in this estimation, counties are not weighted by their number of patients in the health insurance data.

Table 5. Spatial Effects of a 1 SD Higher Therapy Supply among Adjacent County Pairs

	Therapy uptake in b (1)		Therapy uptake in a (2)
Excess supply in a	0.004**		0.023***
	(0.002)		(0.005)
Total effect		0.027	
Local spillover (in %)		15.6	
N (county pairs)	2,044		2,044
Demand type FE	Yes		Yes
County a controls	Yes		Yes
County b-controls	Yes		Yes

Notes: The table contains the results of regressing the share on individuals initiating therapy within one year after discharge on excess therapy supply using county-level data of all adjacent county pairs. The estimates in Column (1) are based on eq. (4) and the ones in Column (2) on eq. (3). In Column (1), the outcome is observed for county b and therapy supply for county a within the adjacent county pair (a, b). In Column (2), the outcome of county a is regressed on its own therapy supply. Both regressions include demand type fixed effects, the county-level control variables listed in Table 3 for both counties in the pair, as well as the excess therapy supply of county b. The standard errors in parentheses are clustered at the county level. The asterisks indicate the significance levels: $^{*} < .10$, $^{**} < .05$, $^{***} < .01$

5.8 Results on the Selectivity of Therapy Recipients

Individuals who initiate psychotherapy following their mental hospital discharge constitute a selective sample: they are disproportionately female, exhibit less severe conditions, and display a higher demand for health investments. Such selectivity can arise from both provider-side screening and patient-side search behavior. Higher therapy supply may attenuate both these selection mechanisms by intensifying provider competition and lowering search frictions, for example, through reduced waiting times or lowering search and commuting costs. We therefore examine whether higher therapy availability alters the composition of patients who receive therapy. For that, we compare baseline characteristics of therapy recipients across regions with high and low therapy supply. Given that higher supply substantially raises therapy take-up, the population of therapy recipients in high-supply regions includes a larger share of supply-sensitive compliers relative to low-supply regions.

To identify compositional changes, we restrict the sample to unit–time observations in which individuals receive therapy and estimate the following regression:

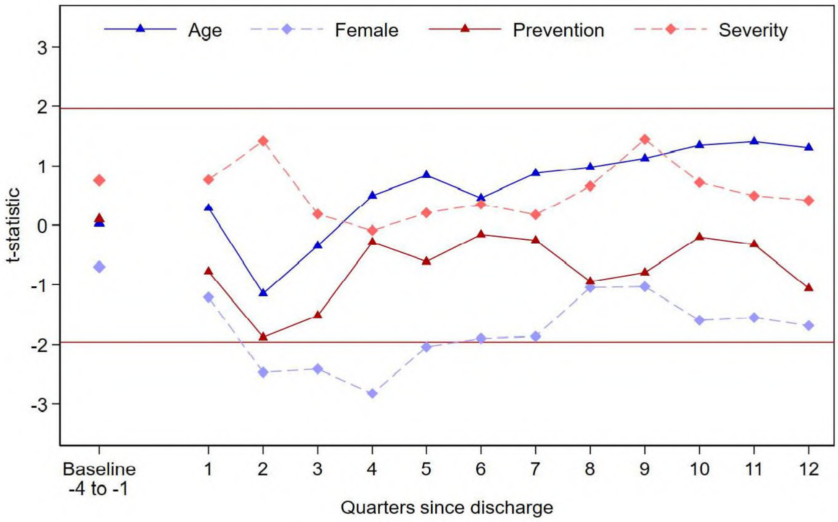
$$y_i^{base} = \vartheta_{td} + \sum_{\tau} \beta_\tau \, 1[t = \tau] \, z_c + \varepsilon_{it} \tag{5}$$

The outcome y_i^{base} is measured during the index mental health hospitalization and thus time-invariant within individual. With the inclusion of the time-by–demand-type fixed effects ,ϑ_{td}, the identification relies on between-unit variation of individuals receiving therapy at the same point in time and within the same demand type. For each quarter since discharge, the coefficients on the interaction between time fixed effects and therapy supply, β_τ, therefore capture whether particular baseline characteristics are more prevalent among therapy recipients in areas with the same therapy demand yet higher therapy supply.

Figure 8 shows t-statistics for testing $H_0 : \hat{\beta}_\tau = 0$ using individuals' demographic traits, three-year readmission risk, and their historic uptake of preventive healthcare as the outcome.[30] Increases in therapy supply only marginally attenuate gender-based selectivity and have no discernible effect on the average case severity of therapy recipients. As a result, although lower-risk patients are overrepresented among therapy recipients, marginal expansions in supply do not mitigate this pattern of negative selection: patients with more severe conditions remain less likely to receive the recommended treatment. Likewise, greater therapy availability does not weaken the strong role of baseline health demand in predicting access to therapy.

[30] Table B1 shows average characteristics of therapy recipients in high- and low-supply areas.

Figure 8. Higher Therapy Supply and the Composition of Therapy Recipients

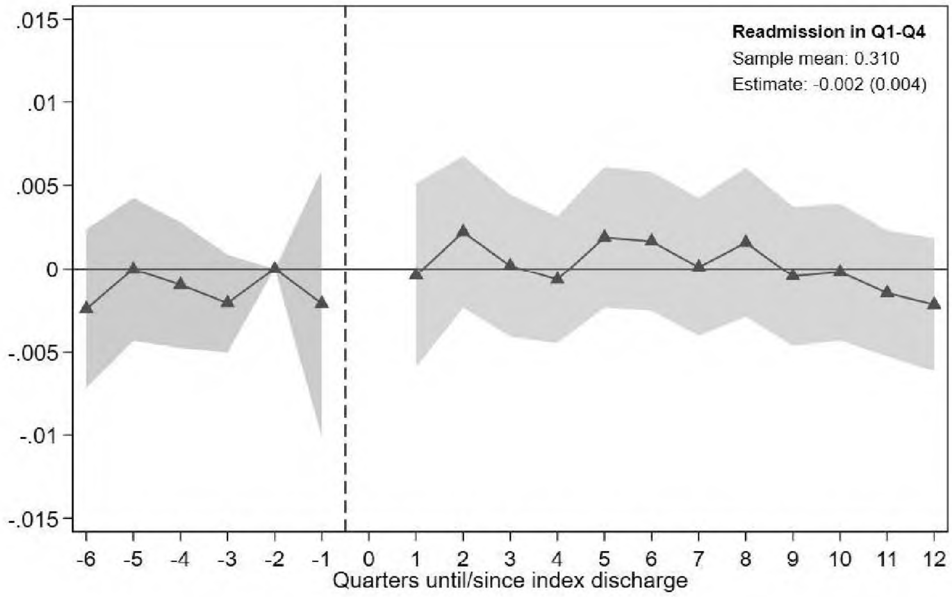


Notes: The figure shows t-statistics of regressing time-invariant individual characteristics on excess supply interacted with quarter since discharge fixed effects using eq. (5). The regressions further include time fixed effects, demand type fixed effects, and regional controls (see Table 3) interacted with time fixed effects. The outcome is denoted by the legend. *Prevention* is an indicator of whether individuals utilized preventive health care (vaccinations or preventive screenings) in the year before their index hospitalization. *Severity* denotes the predicted baseline readmission risk in absence of receiving therapy. The underlying sample only consists of unit-time observations, in which individuals receive therapy. The standard errors are clustered at the county level.

5.9 Results on Hospital Readmission

To explore whether higher therapy availability, which results in increased uptake and marginally shorter waiting times, affects patients' recovery from mental illness, Figure 9 shows reduced form estimates of a 1 SD higher therapy supply on quarterly mental health hospitalization rates. Higher treatment availability does not significantly affect hospital readmission in the short- or long-run. These null results are, however, estimated with low precision, which may be caused by insufficiently strong first-stage effects ($F \approx 32$ for initiating therapy within one year after index hospital discharge). Without conditioning on ill mental health at baseline, recent evidence suggests that psychotherapy reduces psychiatric admission rates by 5 pp (Serena, 2025). In our empirical setting, we cannot statistically identify an effect of this magnitude. Thus, the null results shown in Figure 9 could mask a type II error.

Figure 9. Dynamic Effects of a 1 SD Higher Therapy Supply on Mental Health Hospitalization



Notes: The figure shows effect estimates of higher excess therapy supply on being hospitalized due to mental illness (ICD F00-99) in a given period. The markers depict quarterly estimates produced using eq. (1). The shaded area depicts 95%-level CI. The standard errors are clustered at the county level. The top right corner contains static DiD estimates comparing the mental health hospitalization rates in the year before and after index discharge using eq. (2). The parentheses contain standard errors clustered at the county level.

6 Discussion

We document a market failure where therapy resources are systematically misallocated towards low-risk patients who arguably benefit least, while high-risk patients who could gain the most from treatment are excluded. This negative selection represents an efficiency loss because scarce healthcare resources flow to those with the lowest marginal benefit rather than those who could generate the greatest welfare gains from treatment.

Two mechanisms could generate this negative selection. Provider-side screening allows therapists to choose patients they prefer to treat. The system of constant billing prices thereby fails to internalize that different types of patients can be treated easier than others. Instead, providers are incentivized to select their patients based on factors unrelated to the expected treatment success of the therapy. On the patient side, search costs vary inversely with mental health status. Patients must identify providers, contact practices, and persist through rejections. Severe illness impairs the cognitive resources, making these tasks harder to navigate. In consequence, severely ill patients may be unable to put in the search effort necessary to secure treatment.

Expanding treatment capacity did not reverse this negative selection despite increasing competition and lowering search costs. This finding can be attributed to the underlying institutional context: a healthcare market that is characterized by severe under-supply and provider discretion when selecting their patients. The pool of untreated supply-sensitive individuals with low readmission risk was large enough so that negative selection persisted even in the presence of marginally higher supply. Thus, only once the demand from lower-risk patients is sufficiently exhausted do higher-risk patients systematically benefit from further increasing capacity.

An under-supplied mental healthcare market with free provider choice is not unique to Germany, but present in many other counties. In these countries, our findings challenge the assumptions of supply-side mental health policies, including the US Medicare provider loan forgiveness programs and state-level scope-of-practice reforms. These policies implicitly assume that supply shortages create rationing through delay and that additional capacity will reduce waiting times while serving those most in need. We show that even among recently hospitalized psychiatric patients, where medical need is unambiguous, supply increases do not preferentially reach the highest-risk individuals. If negative selection operates in this high-need context, it likely creates even greater barriers in broader populations targeted by workforce expansion. Effective regulation thus requires attention to micro-level matching mechanisms, not just macro-level capacity planning. Exemplary measures include conditioning reimbursement on serving high-acuity patients or implementing supervised referral systems.

6.1 Beyond Mental Healthcare Markets

Markets with excess demand and provider discretion over client acceptance also exist outside the outpatient healthcare sector. In these markets, negative selection may exists to a similar degree.

A leading example is the (German) market for subsidized childcare, in which providers exercise discretion over enrollment, allowing them to cream-skim families with fewer behavioral challenges or more flexible schedules even though harder-to-serve families may have a greater need. Families with migrant background constitute one group subject to negative selection. Migrant parents utilize public childcare at low rates, despite large potential benefits from childcare due prevalent labor market absences after childbirth. A correspondence study by Hermes et al. (2023) finds that provider-side discrimination contributes to this gap in uptake and the results in losses on the labor market. Expanding childcare supply did, however, not narrow the gap in uptake of public childcare among migrant families (Jessen et al., 2020). Thus, similar to the market for psychotherapy, marginal capacity extensions could not reverse negative selection.

Another example is the market for nursing homes, where providers can systematically exclude patients with complex medical needs who would benefit strongly from skilled care (Gupta et al., 2023). In the US, for instance, nursing homes are reluctant to admit Medicaid patients, particularly those with long expected stays (Gandhi, 2020; Rahman et al., 2014). The structural model in Gandhi (2020) thereby predicts that capacity expansions increase the likelihood that these Medicare patients are admitted to their preferred facilities and, as a result, receive higher-quality care. This finding originates from a market framework in which access to care is fully inelastic to capacity and patients are still admitted to a nursing home without capacity extensions. In light of an aging populating and rising demand for long-term care, negative selection at the extensive margin may become increasingly salient relative to intensive-margin sorting of patients across higher- or lower-quality facilities. If demand sufficiently exceeds supply, patients admitted to nursing homes will already be highly selective in terms of their desirability, and hence their medical need. In this case, marginal capacity extensions may fail to benefit the highest-need individuals and may become less cost-effective.

6.2 Outlook for Future Research

Several questions remain for future research. First, what is the relative importance of demand-side search frictions versus supply-side screening in generating negative selection? Experimental interventions reducing search costs for high-risk patients, or varying reimbursement structures to alter provider incentives could decompose these mechanisms. Second, how do selection patterns vary across institutional contexts? Comparing decentralized systems (Germany, U.S. Medicare Part B) with centralized triage models (UK's IAPT) could reveal whether matching mechanisms or provider incentives drive allocation. Third, what are the long-run consequences of treatment misallocation? Our data show high-risk untreated patients face elevated readmission rates, but we cannot measure broader welfare effects on employment, disability, or mortality that may accumulate over time.

7 Conclusion

This paper documents a fundamental market failure in mental healthcare: a misallocation where resources flow to patients with the lowest marginal benefit instead of those who could gain most from treatment. Despite universal health insurance, clinical guidelines recommendation, and substantial government investments in workforce planning, only 26% of German patients receive psychotherapy within one year of discharge from a mental health hospitalization. Among this select group, those with the lowest predicted risk of relapse are treated over-proportionally, while high-risk patients either receive no treatment or wait longer.

Exploiting quasi-random variation from Germany's therapist licensing system, we show that increasing local supply by one standard deviation largely raises therapy uptake, and marginally reduces waiting times. Supply expansions thus operate primarily through increased patient volume rather than shorter waiting times. In addition, we find that the additional supply is absorbed by lower-risk patients. Thus, decentralized patient-provider matching under excess demand generates persistent negative selection that marginal capacity expansion alone cannot remedy. Only if the demand of lower-risk patients is exhausted can high-risk patients benefit from additional healthcare supply.

Our findings challenge core assumptions underlying contemporary healthcare workforce policy. Policymakers in Germany, the United States, and other high-income countries have responded to mental health crises by expanding provider supply, for example, through training subsidies, scope-of-practice reforms, and loan forgiveness programs, hoping that the additional capacity will reach those most in need. We provide the first causal evidence that such interventions may fail to achieve this objective. Supply expansions benefit marginal patients who look remarkably similar to inframarginal recipients, leaving the allocation mechanism fundamentally unchanged. Our findings thus suggest that expanding workforce capacity, while potentially necessary, is insufficient without addressing the fundamental allocation problem. We argue that these findings are generalizable to other markets with decentralized matching and excess demand, such as the markets for public childcare and long-term care.

When scarce healthcare resources flow to those potentially benefiting the least, society bears costs in both public health outcomes and economic productivity. Recognizing that capacity and allocation operate through distinct channels and require distinct policy interventions represents a critical step towards healthcare systems that serve those most in need.

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Appendix

Contents

A German Treatment Guidelines for Mental Disorders

This section provides an overview of the German clinical guidelines (S3-Leitlinien) for mental disorders classified under ICD-10 Chapter F3-6. These evidence-based guidelines, developed by medical associations and expert panels, inform treatment decisions in the German health-care system and help explain patterns of psychotherapy utilization observed in our data.

F3: Mood (Affective) Disorders

Among all mental disorders, for unipolar depression, the German guidelines offer the strongest endorsement of psychotherapy (DGPPN and BÄK and KBV and AWMF, 2017). The S3 guideline recommends psychotherapy as first-line treatment for mild to moderate depression and as an essential combination treatment with antidepressants for severe depression. CBT, interpersonal therapy, and psychodynamic therapy all receive strong recommendations based on extensive evidence. For bipolar disorder, the guideline recommends psychoeducation and specific psychotherapeutic interventions to improve medication adherence and recognize early warning signs (DGPPN and DGBS, 2019). The high psychotherapy utilization among F3 patients in our sample reflects these strong recommendations and the extensive evidence base showing psychotherapy prevents relapse and reduces chronicity in mood disorders.

F4: Neurotic, Stress-Related and Somatoform Disorders

The treatment guidelines for anxiety disorders, post-traumatic stress disorder (PTSD), and stress-related conditions uniformly recommend psychotherapy as the primary intervention (Bandelow et al., 2021; DeGPT and AWMF, 2021). CBT has the highest level of evidence for panic disorder, generalized anxiety disorder, and specific phobias, with exposure-based interventions showing particularly strong effects. For PTSD, trauma-focused CBT and eye-movement desensitization and reprocessing (EMDR) are specifically recommended, with medication serving only an adjunctive role. The guidelines explicitly state that psychotherapy should be offered to all patients with F4 diagnoses, and our data showing high therapy take-up in this group aligns with these recommendations. The guidelines also note that these conditions often respond rapidly to appropriate psychotherapy, making them attractive to therapists in systems with limited capacity.

F5: Behavioral Syndromes Associated with Physiological Disturbances

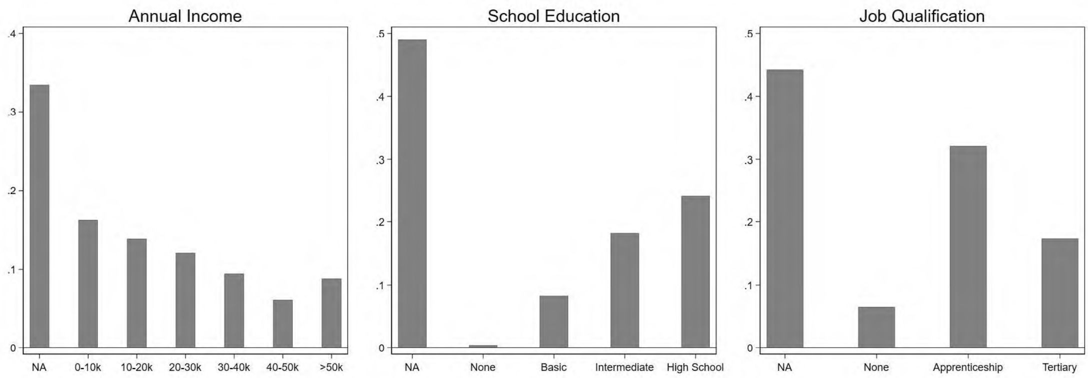
The treatment recommendations for F5 disorders vary considerably by specific condition (DGESS and DKPM and DGKJP and DGPPN and DGPM, 2018; DGSM, 2017). For eating disorders, particularly anorexia and bulimia nervosa, psychotherapy represents the cornerstone of treatment, with family-based therapy for adolescents and CBT for adults showing the strongest evidence. However, severe malnutrition requires medical stabilization before psychotherapy can begin effectively. For sleep disorders, CBT for insomnia (CBT-I) is recommended as first-line treatment. Sexual dysfunctions may benefit from specialized sex therapy, though somatic causes must be excluded first. The heterogeneity within F5 disorders explains the variable psychotherapy utilization patterns associated with them, with high uptake for patients with eating disorders showing but less therapy involvement for patients with other conditions.

F6: Disorders of Adult Personality and Behavior

The German guidelines for personality disorders, particularly borderline personality disorder, strongly recommend specialized psychotherapy as the primary treatment (DGPPN and DGPM and DGKJP and DGPPS, 2022). Dialectical behavior therapy, mentalization-based treatment, and transference-focused psychotherapy have robust evidence bases and receive high recommendations. However, the guidelines acknowledge that effective treatment requires therapists with specialized training and that the therapy must be long-term (often spanning years rather than months). Standard psychotherapy coverage in Germany allows sufficient sessions for personality disorder treatment, but finding appropriately trained therapists presents a major barrier. The guidelines also note that many patients with personality disorders are ambivalent about treatment and show high dropout rates, contributing to the matching frictions we observe in our data.

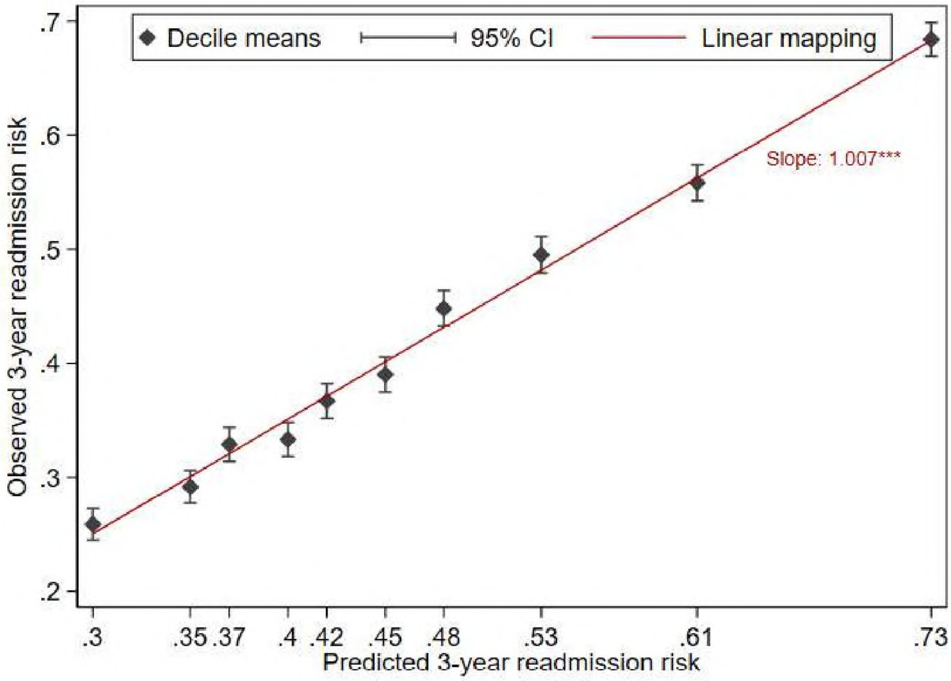
B Additional Empirical Results

Figure B1. Economic Covariates in the Estimation Sample



Notes: The figure shows the distribution of economic characteristics of individuals in the sample in 2016 levels. These economic characteristics are, however, unreliable due to a high share of missing values and infrequent updating.

Figure B2. Binscatter of The Observed and Predicted 3-Year Readmission Risk

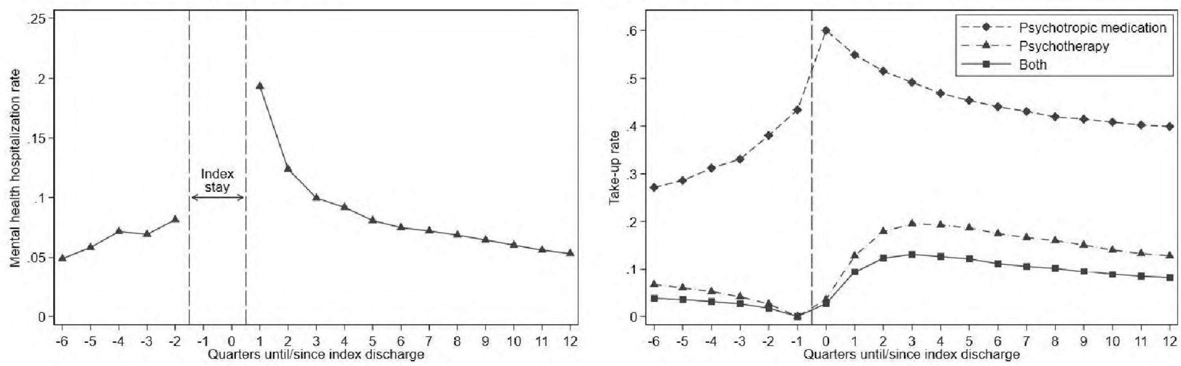


Notes: The figure shows the share of individuals being re-admitted within three years after index hospital discharge across deciles of the predicted three-year readmission risk. Predicted readmission risk is based on a 10-fold cross-validated logit model trained on individuals not initiating therapy within one year after discharge and using individuals' demographic characteristics and medical history as left-hand side variables. The red line depicts a linear fit. The standard errors are clustered at the individual level. The whiskers denote 95% CI. The asterisks indicate the significance levels: * < .10, ** < .05, *** < .01

Figure B3. Readmission Rates and Treatment Uptake by Quarter Since Discharge

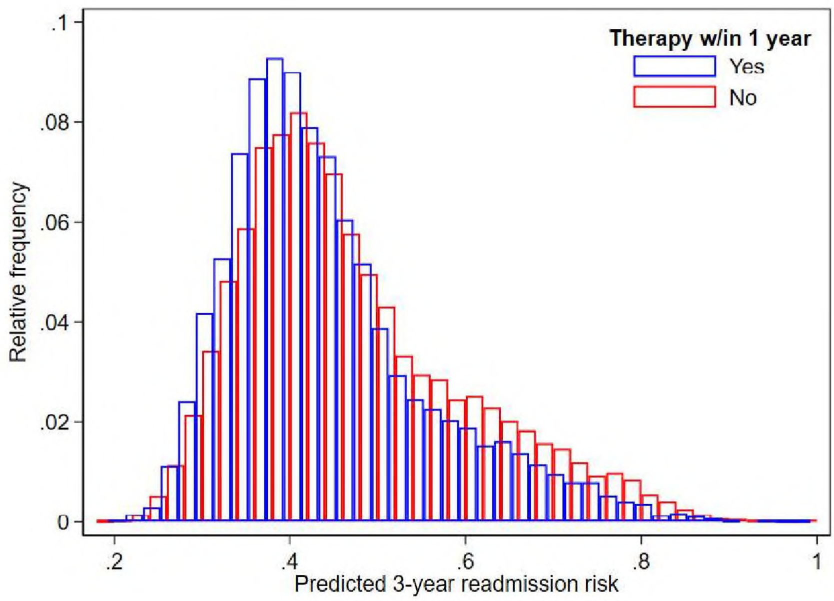
A: Mental Health Hospitalization

B: Outpatient Mental Health Treatment



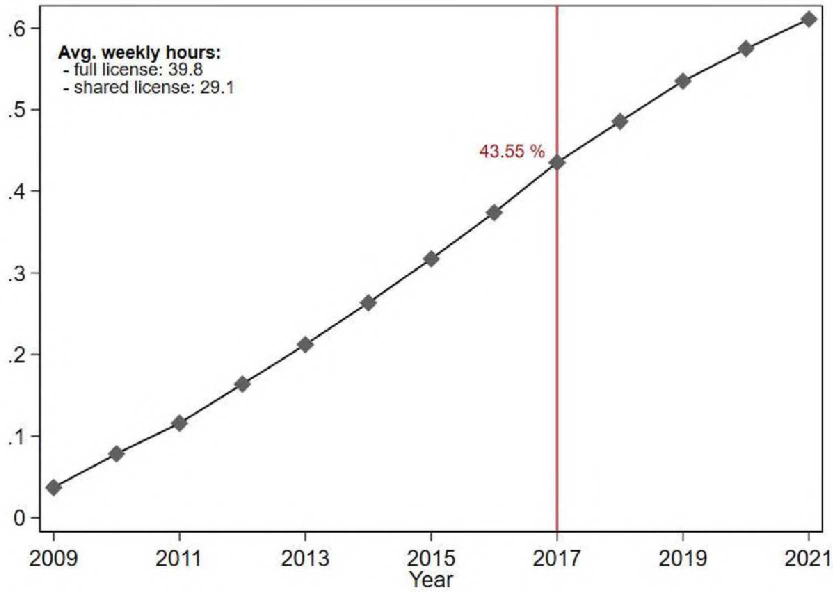
Notes: The figure shows average mental health care take-up rates by quarter since index discharge (quarter 0). The sample excludes individuals receiving therapy during their index hospitalization.

Figure B4. Density of Predicted Readmission Risk by Therapy Uptake



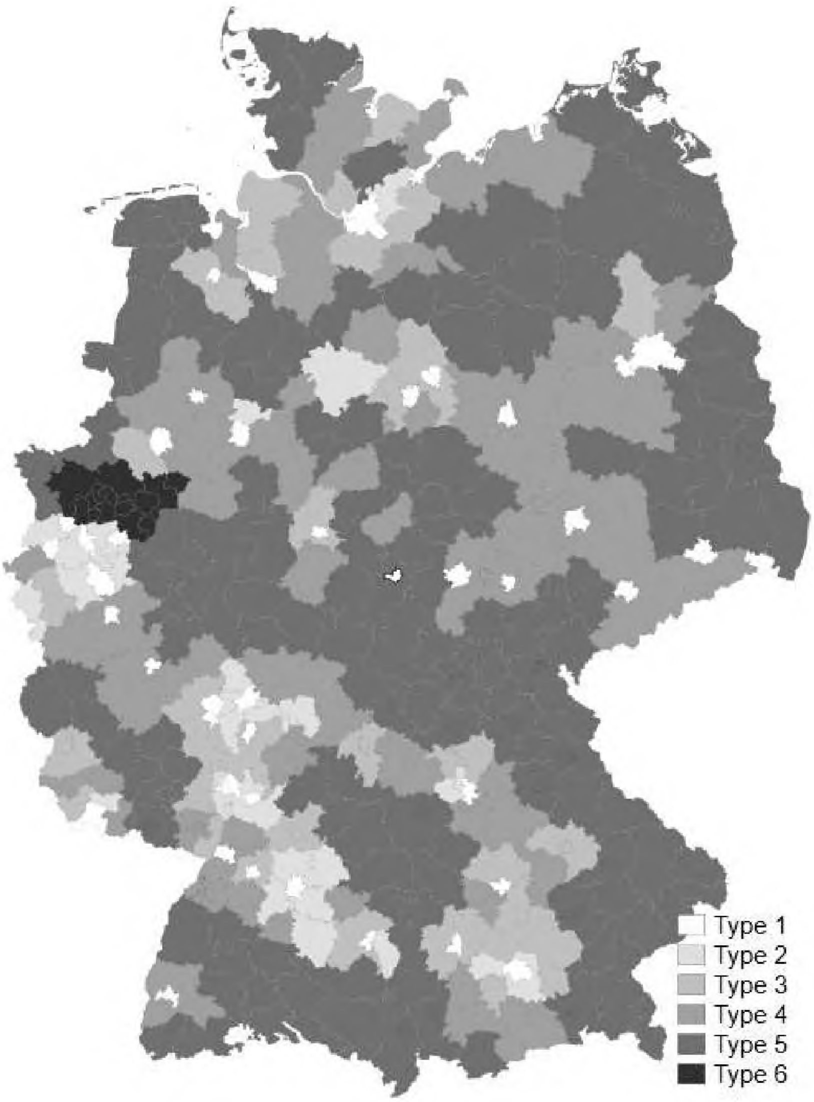
Notes: The figure shows the density of the predicted likelihood of hospital readmission within 3 years after discharge from index hospitalization for individuals initiating/not initiating therapy within one year after index discharge. The predictions are produced using a ten-fold cross-validated logit model using demographic characteristics, diagnoses, and past healthcare uptake as explanatory variables. The model was trained only using individuals who did not receive therapy after discharge.

Figure B5. Prevalence of Shared Licenses over time



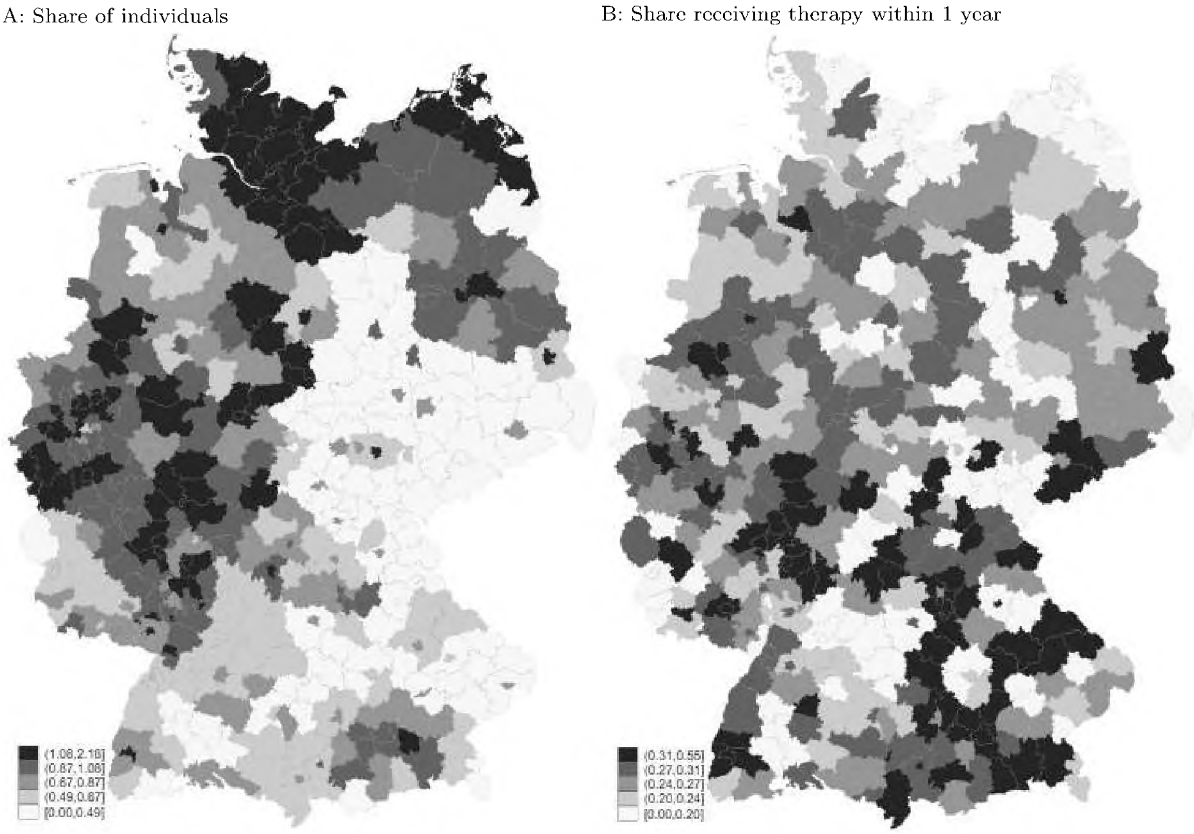
Notes: The figure shows the share of licenses for outpatient psychotherapy that are shared among multiple providers. The red line denotes the year in which all individuals in our sample were hospitalized due to mental illness. Data from: Bundesarztregister (Register of German Practitioners)

Figure B6. Map of Demand Types



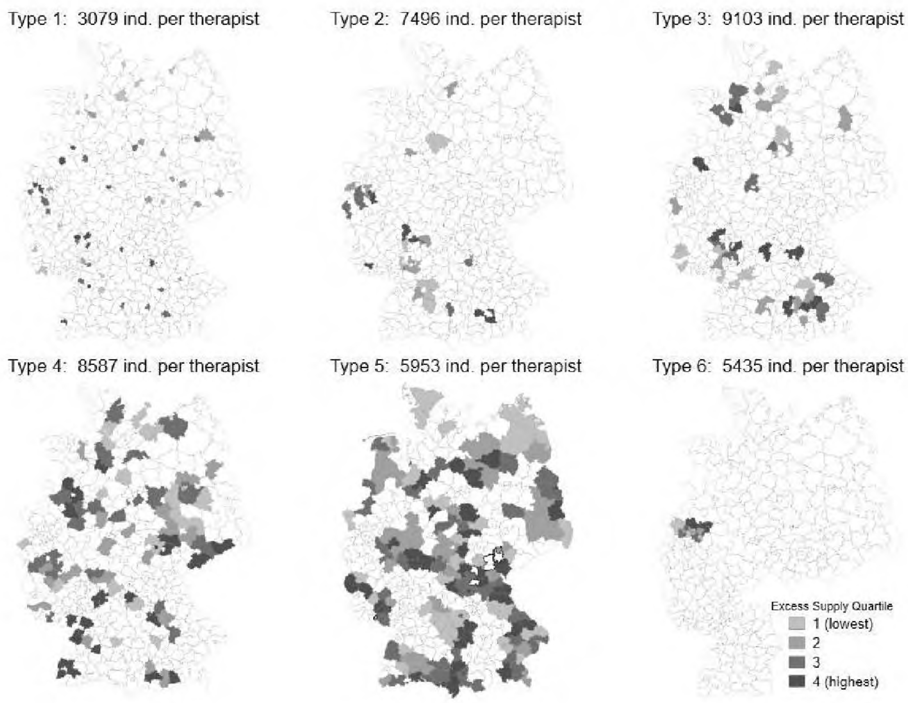
Notes: The figure shows the classification of German counties into the six demand types. Within these demand types, the number of licenses for outpatient psychotherapy per capita is capped at the same level.

Figure B7. In-sample Patients and their Therapy Uptake by County



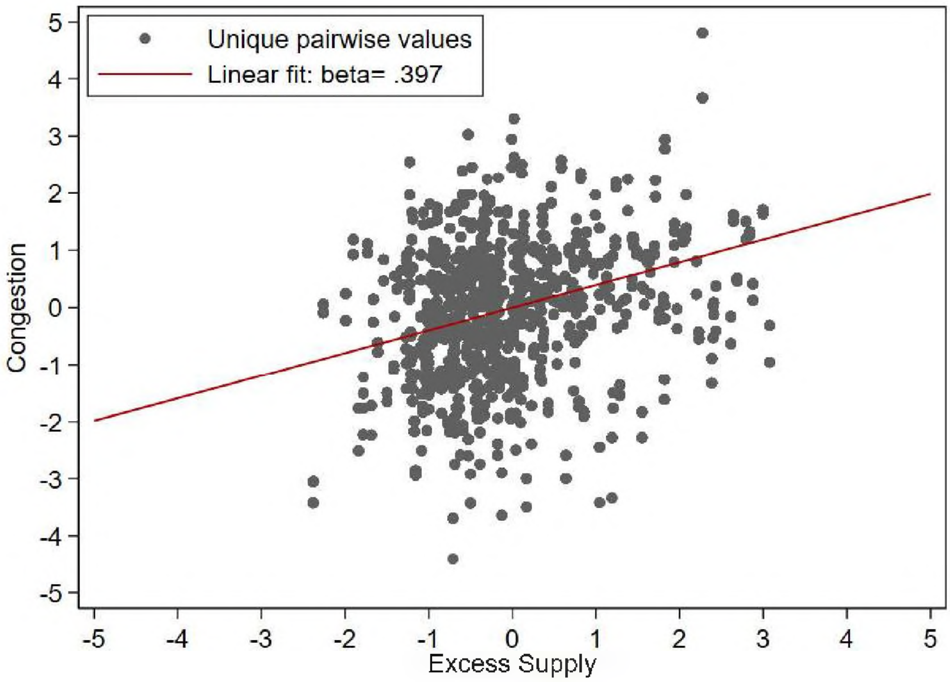
Notes: Panel A shows what share of individuals in the estimation sample (in %) resides in which German county. Panel B depicts what share of individuals residing in a county initiates psychotherapy within one year after index hospital discharge.

Figure B8. Variation in Congestion by Demand Type



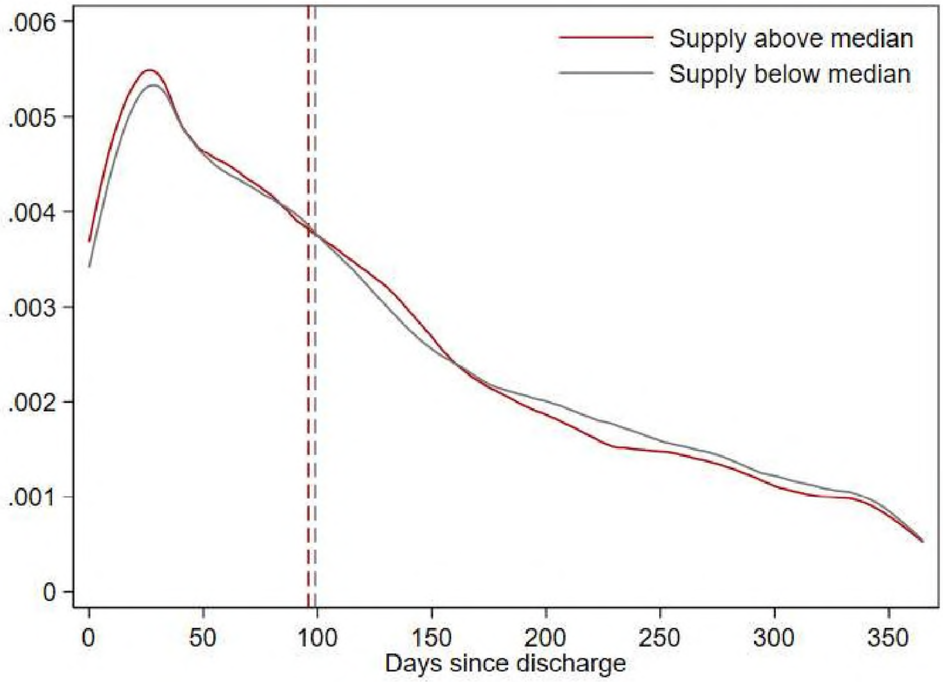
Notes: The maps visualize county-level therapy supply based on the local congestion measure within each demand type in quartiles. The darker (lighter) counties oversupply (under-supply) psychotherapy, with demand for therapy held constant.

Figure B9. Correlation of Excess Supply and Local Congestion



Notes: The figure shows the correlation of the two measures for local therapy supply that are used throughout this paper ($N = 393$).

Figure B10. Density of the Days Between Hospital Discharge and Therapy Initiation

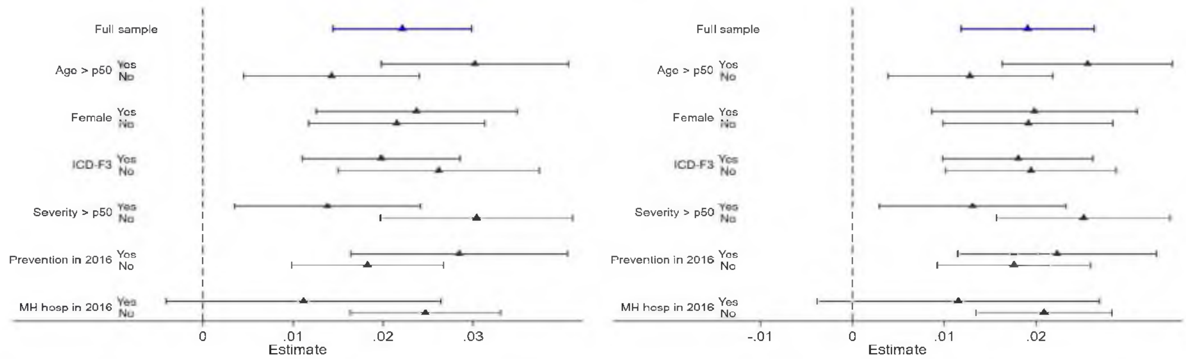


Notes: The figure shows the kernel density of the number of days between discharge from index hospitalization and the initiation of therapy for individuals in regions with above and below median excess therapy supply. The sample consists of individuals initiating therapy within one year after index discharge. The dashed vertical lines denote the group median.

Figure B11. Heterogeneous Effects of a 1 SD Higher Therapy Supply on Treatment Uptake

A: Starting therapy within 1 year

B: Guideline compliance within 1 year



Notes: The figure shows static estimates of higher therapy supply on mental healthcare take-up using eq. (2). In Panel A (B), the outcome is an indicator of whether individuals received any psychotherapy (in combination with psychotropic medication) in the year before or after index discharge. The blue markers denote the effects using the full sample, and the gray markers for using the specified sub-samples. The whiskers depict 95%-level CI. The standard errors are clustered at the county level.

Table B1. Sample Composition of Therapy Recipients by Excess Supply Quintile

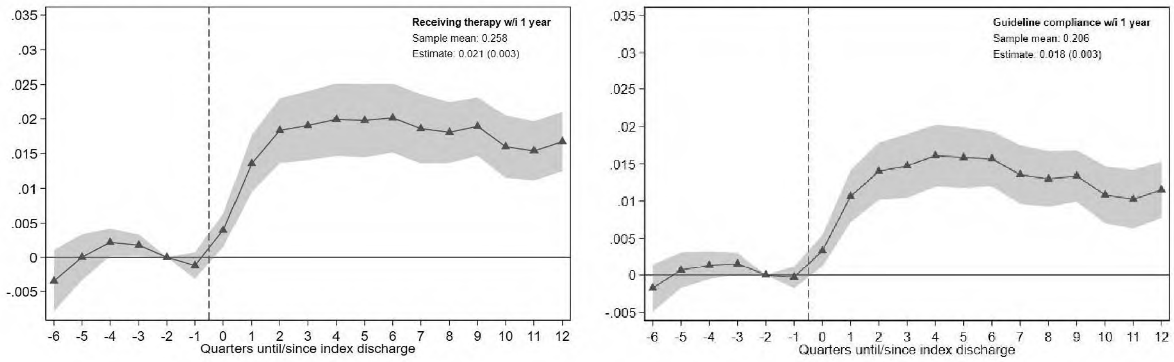
	(1) Supply tercile 1	(2) Supply tercile 3	(3) t-stat Δ
Therapy uptake after hospitalization	0.24	0.28	7.19
Baseline covariates			
Age at discharge	39.85	39.916	0.19
Female	0.688	0.667	-1.76
MH hospitalization in 2016	0.118	0.122	0.50
Psychomedication in 2016	0.607	0.599	-0.68
Baseline relapse risk	0.448	0.45	1.00
Days of index stay	47.491	47.704	0.27
ICD-F3: Mood disorders	0.722	0.709	-1.17
ICD-F4: Anxiety disorders	0.192	0.203	1.14
ICD-F5: Behavioral disorders	0.037	0.038	0.23
ICD-F6: Personality disorders	0.050	0.051	0.14
N	3,210	3,143	

Notes: The table shows the therapy take-up within one year after index discharge and means of baseline characteristics for individuals in the highest and lowest tertile of excess supply within each demand type. Column 3 contains t-statistics of testing for the difference between the group means.

C Robustness Checks and Sensitivity Analyses

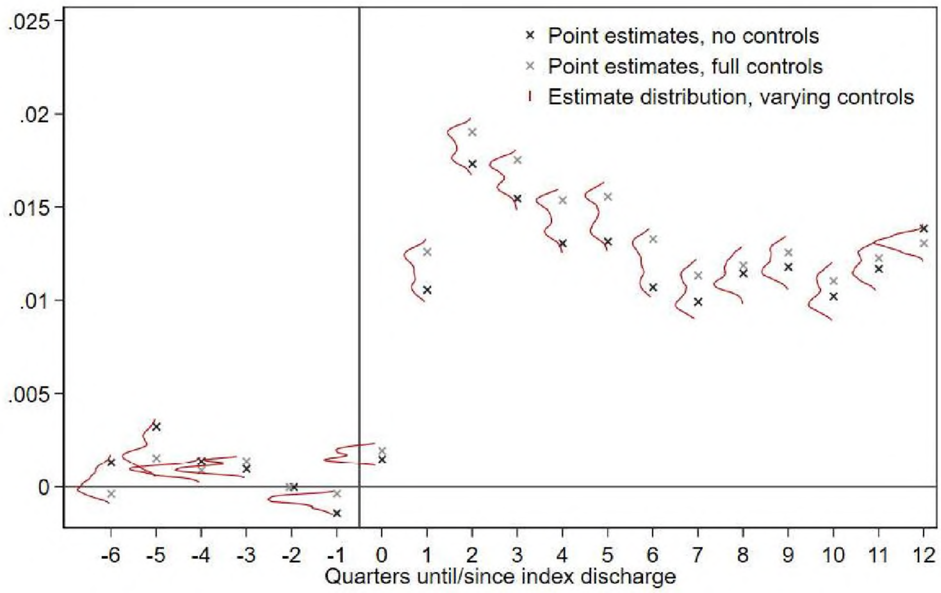
Figure C1. The Effects of a 1 SD Higher Therapy Supply (Local Congestion) on Therapy Take Up

A: Receiving PT B: Guideline compliance



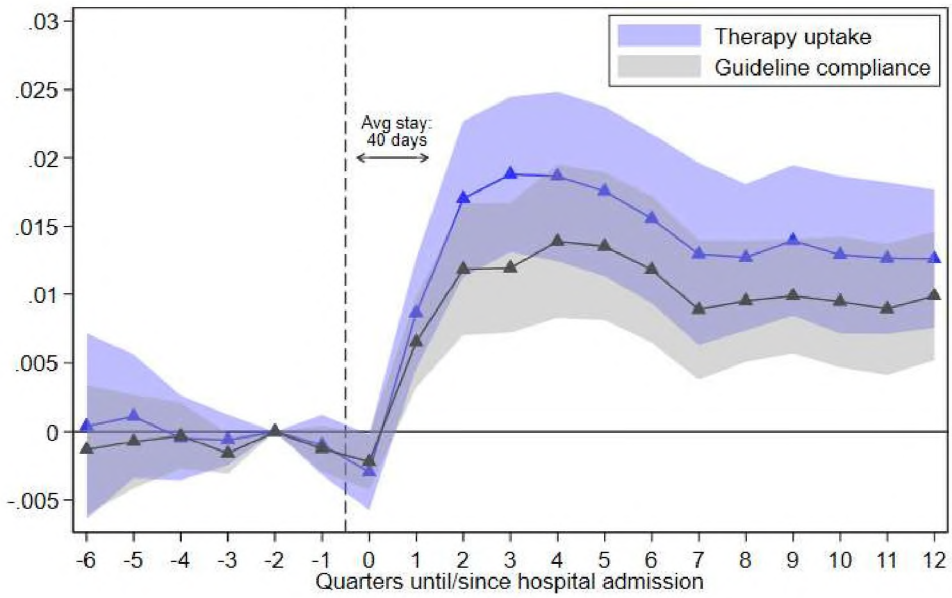
Notes: The figure shows estimates of higher therapy supply measured by local congestion. In Panel A (B), the outcome is an indicator of whether individuals received any psychotherapy (in combination with psychotropic medication) in a given period. The markers depict quarterly estimates produced using eq. (1). The models further include county-level controls (see Table 3) interacted with time fixed effects. The shaded area shows 95%-level CI. The standard errors are clustered at the county level. The top right corner contains static DiD estimates comparing the health care take-up in the year before and after index discharge using eq. (2). The parentheses contain standard errors clustered at the county level.

Figure C2. Effect Sensitivity of a 1 SD Higher Therapy Supply to Varying Covariates



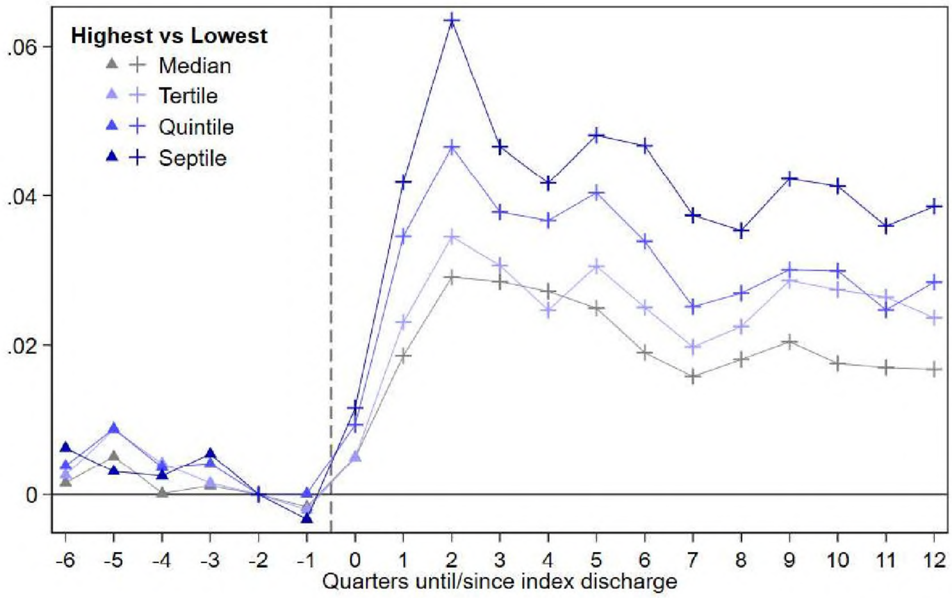
Notes: The figure shows estimates of higher excess therapy supply. The outcome is an indicator of whether individuals received any psychotherapy in a given period. The markers depict quarterly estimates produced using eq. (1). For the dark grey markers, the model also includes county-level controls (see Table 3) interacted with time fixed effects. For the dark grey markers, the model also includes no further covariates. The red lines show the distribution of the period-specific estimates when estimating eq. (1). repeatedly using every possible combination of the available county-level control variables.

Figure C3. The Dynamic Effects of Higher Therapy Supply Relative to Index Admission



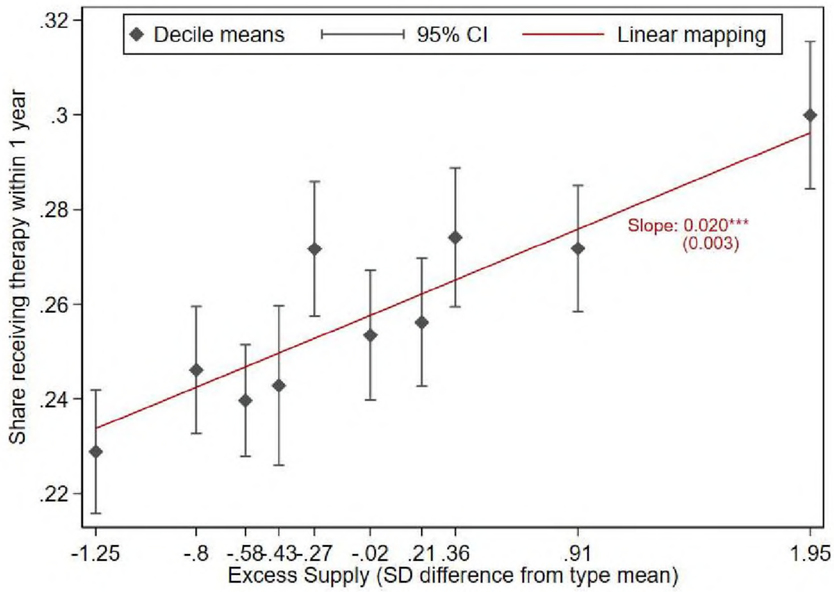
Notes: Analogous to Figure 6, this figure shows estimates of higher excess therapy supply, but relative to the time of index hospital admission. The outcome is an indicator of whether individuals received any psychotherapy (blue coloring) or psychotherapy in combination with psychotropic medication (grey coloring) in a given period. The markers depict quarterly estimates produced using eq. (1). The models further include county-level controls (see Table 3) interacted with time fixed effects. The shaded area shows 95%-level CI. The standard errors are clustered at the county level.

Figure C4. The Effects of Higher Therapy Supply using Binary Comparisons Across Supply Percentiles



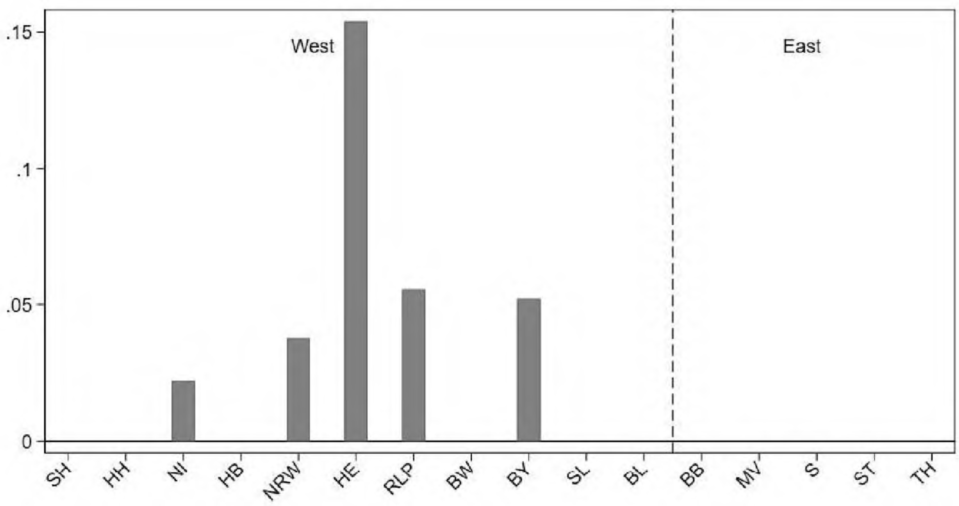
Notes: This figure shows estimates of higher excess therapy supply. Excess therapy supply is transformed into a binary measure. Indicated by the coloring, the sample is restricted to the specified percentiles of excess supply. The outcome is an indicator of whether individuals received any psychotherapy in a given period. The markers depict quarterly estimates produced using eq. (1). The crosses (triangles) denote point-estimates that are (not) statistically significant at the 5% critical level. The models further include county-level controls (see Table 3) interacted with time fixed effects. The standard errors are clustered at the county level.

Figure C5. Excess Supply and Therapy Take-up within 1 Year after Discharge



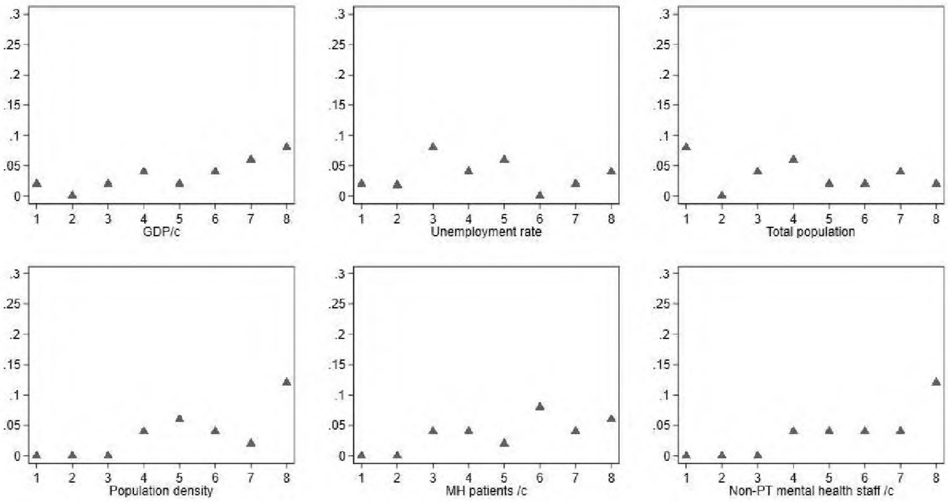
Notes: The figure shows the average take-up of therapy in the year after index discharge by deciles of excess supply. The red line depicts a linear fit. The standard errors are clustered at the county level. The whiskers denote 95% CI.

Figure C6. Share of Excess Supply Outliers by Federal State



Notes: The figure shows the share of counties classified as outliers in excess supply across German federal states. A county is classified as an outlier if its excess supply is outside the 5-to-95 percentile interval.

Figure C7. Share of Excess Supply Outliers by Deciles of Regional Covariates

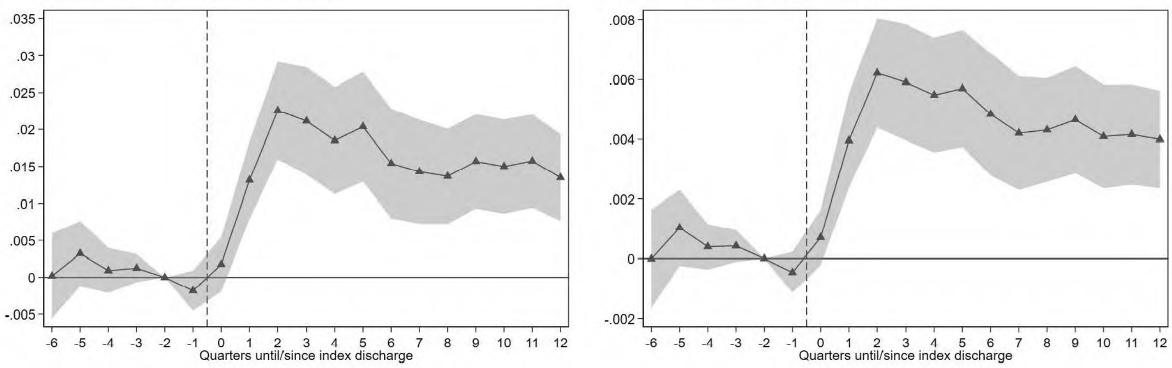


Notes: The figure shows the share of counties classified as outliers in excess supply across deciles of regional covariates. A county is classified as an outlier if its excess supply is outside the 5-to-95 percentile interval.

Figure C8. The Effects of Higher Therapy Supply for Different Outlier Coding

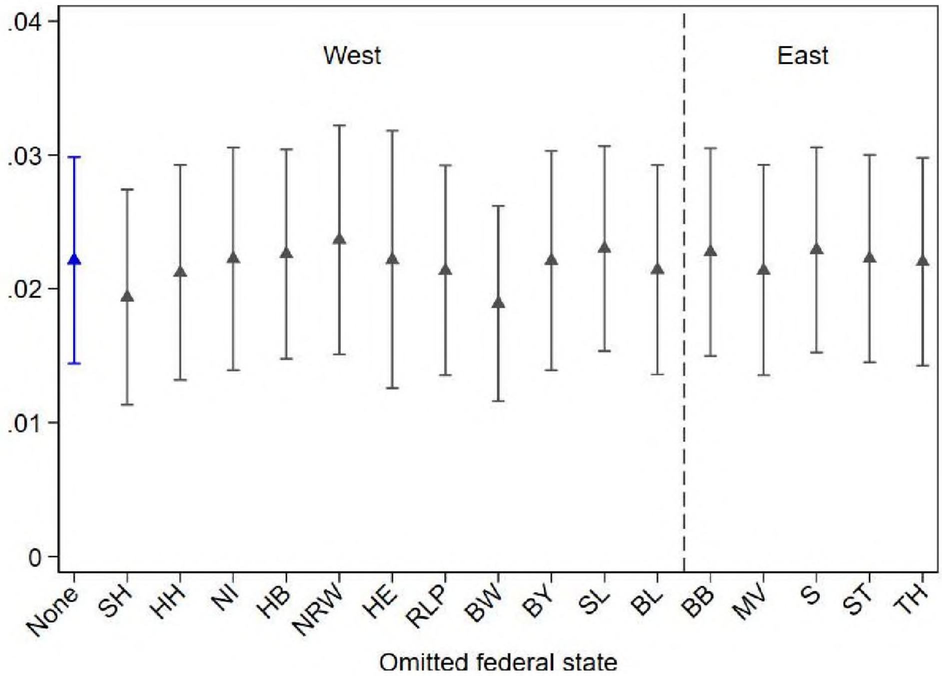
A: Continuous supply, top truncated

B: Effects across supply deciles



Notes: The figure shows estimates of higher excess therapy supply. In Panel A, excess therapy supply is a continuous measure. Counties with excess supply exceeding the 95th percentile are omitted from the sample. In Panel B, excess supply is coarsened into deciles, which are then treated as a continuous measure. The outcome is an indicator of whether individuals received any psychotherapy in a given period. The markers depict quarterly estimates produced using eq. (1). The models further include county-level controls (see Table 3) interacted with time fixed effects. The shaded area shows 95%-level CI. The standard errors are clustered at the county level.

Figure C9. Leave-one-out Estimates of Higher Therapy Supply Across Federal States



Notes: The figure shows static DiD estimates of higher excess therapy supply in the years before and after index discharge using eq. (2). The outcome is an indicator whether individuals utilize psychotherapy in a given period. The whiskers denote 95%-level CI. The standard errors are clustered at the county level. The blue marker corresponds to the main estimate reported in 6. The remaining markers show replications of this estimate while iteratively omitting one German federal state.