Breaking the Cycle? The Role of Psychotherapy after Mental Health Hospitalization

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Abstract

This paper studies the role of psychotherapy in recovery from severely ill mental health. Using rich health insurance data from Germany, we document that utilizing psychotherapy after a mental health hospitalization is associated with lower readmission rates. Yet, there is strong evidence for selection bias. To provide causal estimates, we exploit variation in therapy supply within regions with the same number of federally assigned psychotherapy licenses. Higher therapy supply strongly predicts therapy uptake after hospital discharge both on the extensive and intensive margin. While additional therapy improves adherence to psychotropic medication, we find no beneficial effects on hospital readmission or mental health sick leaves. We provide conclusive evidence that the ineffectiveness of psychotherapy is limited to settings, in which individuals' baseline mental health is low, such as after mental health hospitalization.
JEL-Classification: I01, I11, I18

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1 Introduction

Mental illness is prevalent across the world. In the US, one in five individuals is affected, in Europe one in six (NIMH 2024; European Council 2024). The burden for affected individuals and the economy is immense (i.e., Arias et al. 2022). Once developing mental illness, recovery is rare and individuals are frequently trapped in a vicious cycle of re-occurring episodes of poor mental health (Ali et al. 2017; Hett et al. 2023). During episodes of severely ill mental health, hospitals, such as psychiatric clinics, provide emergency care. Outpatient providers take on follow-up treatment. For most diagnoses, guidelines promote a combination of psychotherapy and psycho-medication. In reality, the uptake of psychotherapy during episodes of poor mental health is low, partly due to government-imposed limits on psychotherapy supply. But also in countries with less regulation, supply shortages prevail. For instance, almost half of the US population is exposed to a designated mental health care shortage (HRSA 2024). Adverse health consequences of these supply shortages are frequently addressed in the public discourse.[1]

A consensus on the effectiveness of psychotherapy has, however, been repeatedly challenged. Existing evidence builds on numerous small-scale RCTs with low power, large signs of publication bias (Cuijpers et al. 2010; Leichsenring et al. 2022), and limited external validity. Non-experimental causal evidence so far only identifies the effect of waiting times for mental health treatment, regardless of the severity of the initial health shock and regardless of the extensive margin choice to utilize treatment at all (Prudon 2024; Oparina et al. 2024). Policymakers are thus insufficiently informed, whether alleviating psychotherapy supply shortages assists individuals in recovering from episodes of poor mental health.

We contribute to filling this gap by identifying whether utilizing psychotherapy after mental health hospitalization helps patients in their recovery. We hereby distinguish between future readmission, adherence to psycho-medication, and sick leaves due to mental health. We also investigate whether psychotherapy particularly benefits certain demographic groups or pathologies. The analysis builds daily claims data from the largest German public health insurance provider, that insures more individuals than the combined population of Denmark and Norway. In particular, the data comprises the full health insurance records between 2016 and 2022 of every individual, that was hospitalized in 2017 due to their mental health.

[1] See i.e. The Guardian (2022) for the US or Sozialverband VdK (2024) for Germany.

We begin by descriptively comparing the mental health-care trajectories of individuals with and without psychotherapy after their hospital discharge. Holding constant demographic characteristics, diagnoses, and severity, psychotherapy following mental health hospitalization is associated with a 2 pp. lower risk of readmission per quarter. Moreover, psychotherapy is associated with better adherence to patients' medication plans, which is one goal of psychotherapy (Sudak and Ayub 2017). However, patients utilizing psychotherapy following their discharge already had more visits with outpatient mental care providers (excluding psychotherapists) and more mental health sick leaves. Thus, the selection of patients with a latent preference for health-care utilization may confound the descriptive benefit of psychotherapy.

To address this selection, we exploit variation in the supply of psychotherapy. In Germany, psychotherapists can only claim insurance money if they are licensed. Each district is thereby provided with a fixed number of licenses based on their past demand for psychotherapy. Aspiring psychotherapists must buy a license from those resigning. However, two districts with the same number of licenses per capita may host a different number of psychotherapists per capita, since licenses can be shared. Based on past evaluations, two psychotherapists sharing a license on average provide 50 percent more working hours (BPtK 2023). Building on the identifying assumption that therapists' preference for working under a shared license is conditionally unrelated to patients' demand for mental health care, we compare patients in areas with the same number of licenses yet varying psychotherapy supply.

The identifying assumption was violated if license sharing was correlated with the local uptake of health care that is unrelated to therapy. One concern may be that psychotherapists are more willing to accept shared licenses in more attractive regions, in which better living conditions also improve mental health. While a region's attractiveness should be internalized in the price of the license, we show that our results are robust to controlling for multiple amenity indices, as well as GDP/c, population density, and an East Germany dummy. Moreover, we show that our variation in therapy supply is not predictive of past mental health care uptake or physical health care uptake at any point in time. Also, we control for per capita outpatient mental health providers (excluding psychotherapists) to avoid that therapists crowd-out substitute providers.

We find that increased psychotherapy supply strongly predicts its uptake after mental health hospitalization, particularly on the extensive margin. Increasing the hours-adjusted supply by 10 percent increases the uptake within a year by 1.6 percentage

points. Conditioning on the uptake of treatment, such as Prudon (2024), a higher supply of psychotherapy increases the number of sessions within the year after discharge, which is mostly driven by fewer days between therapy sessions and weakly driven by shorter waiting time for initial treatment.

Focusing on secondary health outcomes, we show that coincidentally to the higher uptake of psychotherapy, psychotropic drug uptake increases. Benchmarking both effects yields the IV estimate that psychotherapy increases drug adherence by 18 pp. Note that this figure may be bloated since the additional therapy supply also increases the frequency of therapy on the intensive margin. For hospital readmission rates, in contrast, we find no beneficial effects of increased therapy supply; neither in the short-run, when individuals commit to therapy, nor three years after the index discharge. Thus, we find no mental health benefit of psychotherapy after hospital discharge. The null results are precise, robust, and homogeneous across types of patients.

These findings advance our limited understanding of the effectiveness of psychotherapy in treating severe cases of mental illness. So far, a myriad of trials from the medical literature provide a wide range of results with a dubious quality (Leichsenring et al. 2022). Recent field experiments from the economic literature find positive mental health effects of psychotherapy among expecting mothers with depression in Pakistan (Baranov et al. 2020, Sevim et al. 2024).[2] Using observational data, Serena (2024) shows that financially incentivizing psychotherapy improves mental health outcomes in Denmark. Oparina et al. (2024) compare individuals receiving psychotherapy with wait-listed candidates, and show that self-reported mental health improves during therapy. In contrast, this paper shows that psychotherapy does not necessarily improve mental health. We explore two mechanisms that may explain why our results deviate from the current belief on the effectiveness of psychotherapy.

First, recent evidence suggests the benefit of psychotherapy lies in preventing mental health deterioration (Barker et al. 2022). For individuals with active mental illness, preventative effects may be absent mechanically, due to their already low mental health. To test this mechanism, we focus on a sample with better mental health. Replicating the empirical approach of Oparina et al. (2024), we also find significant

[2]Other RCTs target a more general population without screening for baseline mental illness, such as Barker et al. (2022) (Ghana), Bhat et al. (2022) (Kenya), Haushofer et al. (2020) (Kenya) and Vlassopoulos et al. (2024) (Bangladesh). Heller et al. (2017) (Chicago), Blattman et al. (2017, 2023) (Liberia) and Ghosal et al. (2022) (India) investigate the effects of psychotherapy on vague proxies for mental health.

health benefits of psychotherapy.

As such, this finding has crucial implications for the emerging literature, that incorporates mental health in structural models.[3] Both workhorse models on health investments, the health capital (Grossman 1972) and health depreciation (Dalgaard and Strulik 2014) model, assume independence of the returns of health investments and the health/deficit stock. Accordingly, Cronin et al. (2024) and Roth et al. (2024) impose universal effectiveness of therapy, which leads them to the conclusion that individuals under-utilize therapy due to biased beliefs. Contradictory, our findings rather dictate a design, in which the returns of mental health investment are endogenous with respect to the agent's baseline mental health stock such that the marginal gain of investment is low(-est) in the left-most tail of the mental health distribution. Thus, individuals being stuck in an equilibrium of ill mental health may not be caused by uninformed decision-making but rather by a lack of effective treatment options.

Second, there may exist selection into treatment based on expected treatment success. Observational evidence on the benefits of mental health treatment only stems from populations that pre-selected into mental health treatment, regardless of its supply (Oparina et al. 2024; Prudon 2024; Williams and Bretteville-Jensen 2022). Our null results, in contrast, are local effects on compliers, hence individuals, whose therapy uptake is supply-sensitive. This supply-sensitivity may stem from individuals' private information on their treatment success. If treatment success was correlated with observable factors, and only always-takers benefit from therapy, then compliers and always-takers would differ from one another. This is, however not the case, suggesting this channel may be incidental. Still, one should be cautious when extrapolating the effects of therapy stemming from pre-selected samples onto individuals that decide not to utilize therapy based on private information.

This paper also contributes to the literature on the supply and demand for (mental) health care. Shapiro (2022) shows that inducing demand through advertisement increases the uptake of mental health treatment. On the supply side, recent studies argue that congestion of the outpatient care system primarily affects waiting times (Prudon 2024; Williams and Bretteville-Jensen 2022). We add that healthcare supply is not only predictive of treatment delay but also of treatment intensity, measured as the number of sessions in a given time frame. Even more so, there is a large extensive margin response on treatment uptake that had yet to be documented. With that, we provide another piece to the puzzle of why many patients qualifying for psychother-

[3] See Adda et al. (2024), Cronin et al. (2024), Jolivet and Postel-Vinay (2024) and Strulik (2019).

apy do not utilize it, even if covered by universal health insurance (Cronin et al. 2024; Roth et al. 2024).

2 Psychotherapy in Germany

Psychotherapy is a common form of outpatient mental health treatment. Psychotherapy is both used to prevent mental illness and to treat acute episodes of ill mental health. As such, psychotherapy is a recommended outpatient treatment for most diagnoses of severely ill mental health. Appendix A provides a detailed overview of mental health diagnoses leading to hospitalization and the follow-up treatment recommended by guidelines.

To work as a psychotherapist in Germany, individuals must meet stringent academic and professional criteria governed by the Psychotherapeutengesetz (Psychotherapists Act). First, individuals must obtain a 5-year university degree in psychology or medicine. The former qualifies for becoming a psychological therapist and the latter for becoming a medical therapist. Then, individuals must absolve a specialized postgraduate apprenticeship, which includes theoretical instruction and practical experience.[4] This training is typically provided by state-recognized institutions and encompasses supervised practice in clinical settings.[5] Passing the apprenticeship's final exam legally allows individuals to practice as psychotherapists both in an inpatient clinic or as an outpatient provider.

In 2017, there exist 44 thousand psychotherapists in Germany, 80% of whom are psychological therapists (ZI 2021). The treatment repertoire of psychological therapists only consists of talk therapy, whereas medical therapists can also prescribe medication or order paid sick leaves. In reality, individuals' pharmaceutical mental health treatment is, however, typically governed by a psychiatrist.

Over 70% of psychotherapists work in outpatient practices (German Statistical Office 2021). The services provided in these practices are available to individuals without any gatekeeper institution. If the practice is licensed (see Chapter 3.3), treatment is fully covered by patients' universal health insurance.[6] However, waiting times are

[4] Until 2024, the apprenticeship for child and adolescent psychotherapy was also open for individuals holding other university degrees, such as in social work.

[5] A recent reform integrated the apprenticeship into the university degree for individuals starting their study in 2024 onward.

[6] The price of therapy is fixed through the Uniform Value Scale (Einheitlicher Bewertungsmaßstab) that is set by the Kassenärztliche Bundesvereinigung (KBV) a commission of representatives from physicians and public health insurance providers.

long with a median of 139 days between first contact and treatment (Germany Federal Parliament 2022). Waiting times may be shorter if patients pay out-of-pocket. Based on small-scale survey results, 9% of individuals ever having received psychotherapy utilized therapy without insurance coverage (SOEP-IS Group 2021). Another rationale for self-financing therapy is hiding mental health diagnoses from official records since some diagnoses disqualify individuals from certain jobs or insurances. Also, if patients can attest that no treatment options are available, the health insurance may reimburse the out-of-pocket spending at unlicensed psychotherapists.[7]

3 Data

This paper relies on data from one of the largest public health insurance providers in Germany. Approximately 90% of the population is insured through the public health insurance system. Public health insurance is provided by several non-profit companies, that individuals can choose from. Across public health insurance providers, the coverage is uniform. The list of covered services includes inpatient and outpatient treatments, prescription medication, and earnings compensation during sick leaves.
The data comprises all insurance takers above the age of 18 that were hospitalized in 2017 due to their mental health.[8] We refer to the hospitalization that was decisive for sample inclusion as index hospitalization. For the time between 2016 and 2022, we have daily information on individuals' healthcare uptake that was at least partly covered by insurance, including 3-digit ICD diagnoses, costs and duration of treatments, and unique identifiers for hospitals, outpatient practices, inpatient and outpatient doctors, and mental healthcare providers. We convert this data from its original spell format into a panel in which we accumulate healthcare uptake on the quarterly level.
Moreover, the insurance data provides a list of all licensed psychotherapists and other mental health care providers that can be linked to patients' insurance records. Additionally, we complement the data with district-level economic measures from the German Statistical Office, as well as two amenity indexes that rank German districts based on their demographic and socio-economic attractiveness (Prognos2016).[9]

[7]The health insurance companies decide on these types of reimbursement on a case-by-case basis with uncertain outcome.

[8]The main diagnosis of the stay must fall into ICD-10 F01 to F99. Hospitalizations with a mental health side-diagnosis only are not considered a mental health hospitalization.

[9]These include the local GDP/c, population density, and the per-capita mental health hospitalizations (across all insurance providers). The amenity ranking for demography is based on local

In general, German health insurance data is of high quality. Since health-care providers are directly paid by the insurance, they have a high incentive to file the claims thoroughly. For sick leaves, this is, however, not the case. Sick leaves shorter than 42 days are compensated by the employer. Individuals are mandated to inform their insurance of their sick leave by sending a certificate previously received from their GP to the insurance company. In reality, this is however not enforced and workers still receive their compensation if they do not comply. Thus, we only observe sick leaves conditional on patients' sending the certificates to the insurance.

3.1 Sample

The raw sample contains the full insurance records from approximately $77,000$ patients. A handful of these individuals were not hospitalized in 2017, have missing information on their area of residence, or have a faulty person identifier, hence we drop them. From the remaining 76,271 individuals, we also drop those already in therapy during the quarter of their index hospitalization, those switching health insurance before 2021, and those hospitalized due to mental health conditions unsuited for psychotherapy (ICD F1,7,8).[10]

The cleared sample consists of $64,8007$ individuals. Column 1 of Table 1 provides some descriptive statistics.[11] Mood disorders, such as major depression and bipolar disorder (ICD F3) are the leading case of mental health hospitalization. The duration of the index hospitalizations varies largely. Its distribution is right-skewed, with a median stay of 30 days. After the discharge, therapy uptake is low considering it is recommended for all diagnoses. A quarter (tenth) of patients begins therapy within a year (90 days) after discharge.

Column 2 shows descriptive statistics of patients starting therapy within a year. These individuals are more likely female and mood disorders are even more prevalent. We match these individuals $1:1$ to those not starting therapy in the year after their discharge based on the covariates shown in Table 1.[12] Column 3 shows covariate means of the matches, which mirror the ones in Column 2.

fertility and population age. The ranking for socio-economics is based on purchasing power, crime rates, public debt, and the share of individuals cohabiting for economic reasons (Prognos 2016).

[10] Those include disorders due to known physiological conditions (such as dementia), intellectual disabilities, and development disorders.

[11] The insurance data also contains labor market characteristics, yet unfortunately those are missing for $40-60\%$ of patients (see Figure A.1).

[12] We match exactly on gender, 1-digit diagnoses of the index hospitalization and whether they were hospitalized in 2016, based on their propensity score using age and the duration of the index hospitalization as independent variables.

Analogously, Columns 4 and 5 contain information on individuals utilizing therapy and their matches for whom we observe at least one sick leave. While this is the case for only 80% percent of the initial sample, comparing Columns 2 and 4 shows no large signs of selection. Nevertheless, results on sick days should be taken with a grain of salt.

Table 1. Summary Table

	Full Sample			Sickday Sample	
	(1)	(2)	(3)	(4)	(5)
	Full	Therapy	Matched	Therapy	Matched
Female	0.54 (0.50)	0.68	0.68	0.67	0.67
Age	45.69 (16.80)	42.85	42.78	42.10	41.68
Preceeding MH hospitalization	0.21 (0.40)	0.16	0.16	0.15	0.15
Index Hospitalization					
Duration (Days)	36.32 (32.95)	43.97	43.55	43.62	43.25
ICD-F1: Substance abuse	0.17 (0.38)	0.04	0.04	0.04	0.04
ICD-F2: Schizophrenia	0.11 (0.31)	0.04	0.04	0.04	0.04
ICD-F3: Mood disorders	0.46 (0.50)	0.64	0.64	0.67	0.67
ICD-F4: Anxiety disorders	0.14 (0.34)	0.18	0.18	0.18	0.18
ICD-F5: Behavioral syndromes	0.04 (0.19)	0.03	0.03	0.03	0.03
ICD-F6: Personality disorders	0.05 (0.22)	0.04	0.04	0.04	0.04
ICD-F9: Childhood disorders	0.04 (0.19)	0.02	0.02	0.01	0.01
Therapy Uptake					
Within 90 days	0.09 (0.29)				
Within 365 days	0.24 (0.43)				
Ever after hospitalization	0.33 (0.47)				
N	64807	15363	15363	12482	12482

Note: The table shows sample means and standard deviation (in parentheses) of the sample used in this paper. Column 1 provides an overview of the full sample after applying sample restrictions. Column 2 contains only individuals starting psychotherapy within a year after their discharge and Column 3 contains their $1:1$ matched comparison without therapy. Columns 2 and 3 form the matched sample. Columns 4 and 5 provide the analogue using the sub-sample of individuals with information on their sick leaves.

3.2 The Association of Psychotherapy and Recovery from Mental Health Hospitalization

As a starting point, we contrast the quarterly mental health care uptake of individuals utilizing therapy in the year after their discharge and their matched comparison units in Figure 1. All patients are thereby discharged from their index hospitalization in period 0. Panel A shows the share of individuals having filed a prescription for

psycho-medication per quarter since discharge. Until their index discharge, medication uptake aligns between the groups. Shortly after the index discharge, two thirds of individuals utilize psychotropic drugs; a low fraction considering psycho-mediation is a recommended treatment for all major diagnoses. After the discharge, a gap opens and individuals utilizing psychotherapy are 5 pp more likely to file a psychotropic drug prescription.

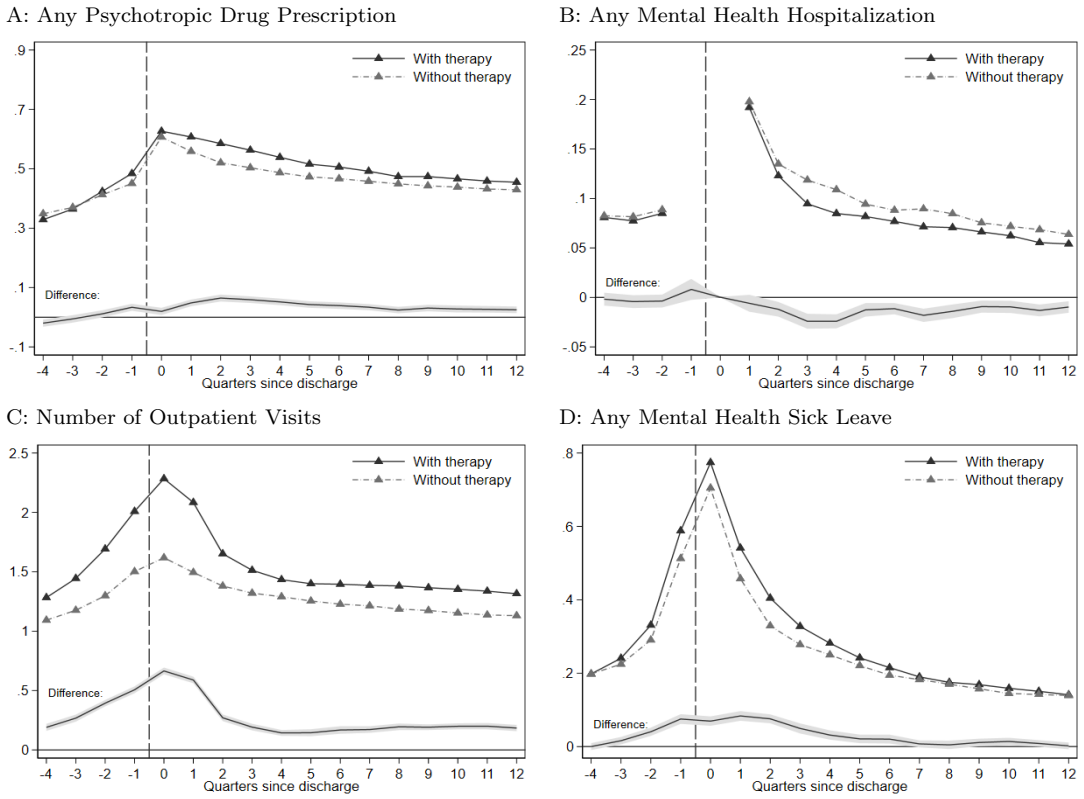
Panel B shows quarterly hospitalization rates with a mental health condition as the leading diagnosis. In quarter zero, all individuals are hospitalized by construction. The panel highlights that relapse rates are high. In the first quarter after the index discharge, 20% of individuals are readmitted to a hospital. In the following quarters, a gap opens, and those utilizing therapy are 3 pp less likely to be readmitted in a given quarter. Thus, psychotherapy in the year after discharge is associated with better adherence to medication guidelines and lower risks of relapse. This association may, however, be driven by selection bias. The bottom panels of Figure 1 uncover that patients starting therapy after their discharge have more appointments with outpatient mental health-care providers (excluding psychotherapists) and a higher likelihood of mental health sick leaves in 2016. Thus, individuals utilizing therapy are already more attached to the healthcare system. An unobserved preference for healthcare usage may thus confound the uptake of therapy and future mental health, forbidding a causal interpretation of the above-stated associations.

3.3 Variation in Psychotherapy Supply

To causally investigate the effectiveness of therapy after mental health hospitalization, we leverage variation in therapy supply. To regulate therapy supply the Kassenärztliche Bundesvereinigung (KBV) handed out a fixed number of licenses to sustain a target therapist-per-population-ratio. These licenses authorize outpatient therapists to claim money from any public health insurance. Licenses are district-specific and trade-able, so that aspiring therapists must buy the license off a retiring therapist from the same district, in which they want to practice.

The number of licenses per capita in a district is based on its past demand for outpatient healthcare and based on whether the district supplies (demands) healthcare for (from) surrounding areas. Particularly, the KBV classifies districts into 6 demand-types with unique licenses-per-capita ratios (see Figure 2 for a map). Thus, the observed ratio of licensed therapists per capita S_k of district k in demand-type d should thus (roughly) equal the average therapist-per-capita ratio $\bar{S}_d$ of demand-type d. The percentage deviation of a district's observed ratio from its demand-type's

Figure 1. Average Mental Health-Care Utilization by Quarter since Discharge



Note: The figure shows group means and their difference by event time for individuals starting psychotherapy within the year after their discharge and their matched comparison group. The discharge occurs in quarter 0. The shaded area denotes 95%−level confidence intervals. The standard errors are clustered at the district level.

average is thereby given by:

$$D_{d_{(k)}} = \frac{S_k - \bar{S}_d}{\bar{S}_d} \cdot 100 \tag{1}$$

In theory, $D_{d_{(k)}}$ should be near zero $\forall k$, yet in reality it is not. For that, there exist two mechanical reasons. First, since demand for mental health care is low among the elderly, the KBV hands out additional licenses if the share of individuals below age 65 in a district is lower than the share in Germany (Federal Joint Committee 2017).[13] Secondly, the licensing system is slow to adjust to population growth. If a district's population shrinks, S_k increases, yet only if S_k exceeds the district's target ratio by 140 percent, the KBV starts retracting licenses. To partial out this demographic variation in therapy supply, we regress $D_{d_{(k)}}$ on the age adjustment factor used by the KBV to hand out additional licenses and on population growth. The residual, hence the variation in supply unexplained by demography, is henceforth defined as excess supply:

$$ExcessSupply_{d_{(k)}} := \hat{\varepsilon} = D_{d_{(k)}} - \hat{\beta}_1 Agefactor_k - \hat{\beta}_2 \Delta Pop_k \tag{2}$$

Despite accounting for demographic variation in supply, districts with the same target ratio of therapists per capita may still provide varying therapy supply. That is due to psychotherapists being allowed to share a license. In 2017, 44% of therapists worked a shared license (see Figure A.2). Under a shared license, weekly therapy hours are capped at 25. Still, therapists under a shared license on average work 29.1 weekly hours (including time for preparation and documentation), while therapists under a full license on average work 39.8 weekly hours (BPtK 2023). Thus, per-license labor supply increases by 50% if the license is shared.

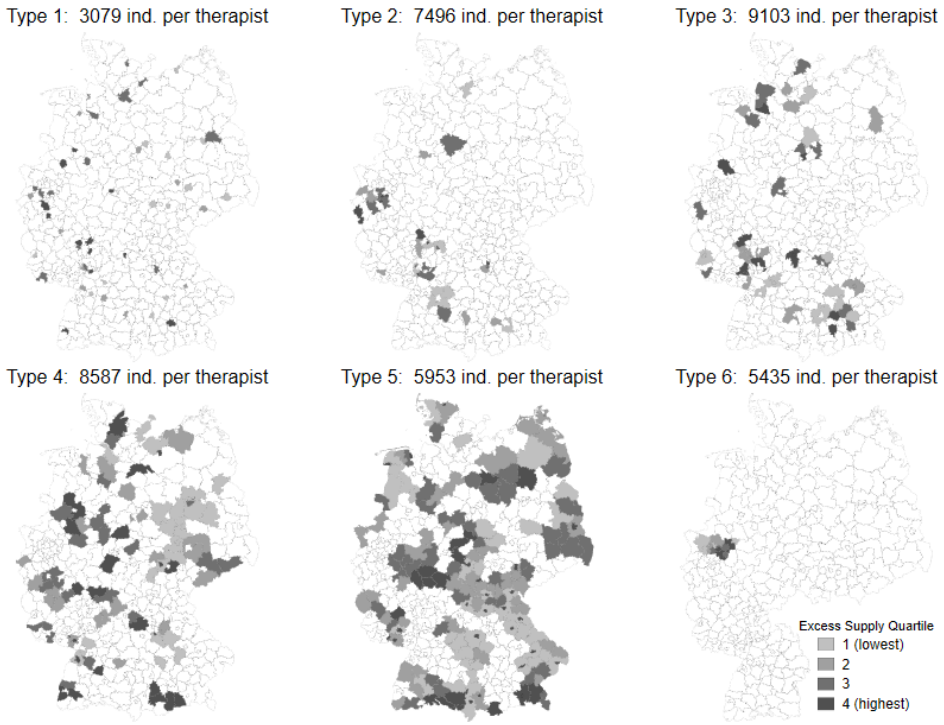
The variation in psychotherapy supply in 2017 is visualized by the coloring in Figure 2. In the dark grey areas, excess supply exceeds the median and in the light grey areas, it lies below the median. The empirical strategy of this paper relies on comparing light and dark areas within the six maps. In addition, Panel A of Figure 3 shows the raw distribution of excess therapy supply. The measure follows a bell-shaped pattern centered around zero. However, there exist some outlier districts with an exceptionally high supply. These outliers are particularly small in population, so

[13] Practically, the KBV scales each district's target ratio by the factor $\frac{Young_{DE}+Old_{DE}\cdot 0.135}{Young_k+Old_k\cdot 0.135}$, where $Young_{DE}$ (Old_{DE}) is the share of individuals below (above) age 65 in Germany and $Young_k$ (Old_k) the share in district k .

that marginal changes in the number of therapists may have large effects on the per-capita therapy supply (see Figure A.4 and A.5).

Intuitively, the link between therapy supply and therapy uptake is weaker in the right tail of the supply distribution than it is in its center.[14] The outliers thus attenuate the overall link between therapy supply and uptake towards zero. To address this concern, we censor excess supply at |100| in our main specification, yet we show our results being robust to truncating outliers, converting the excess supply variable into deciles, and using the variable in its raw form.

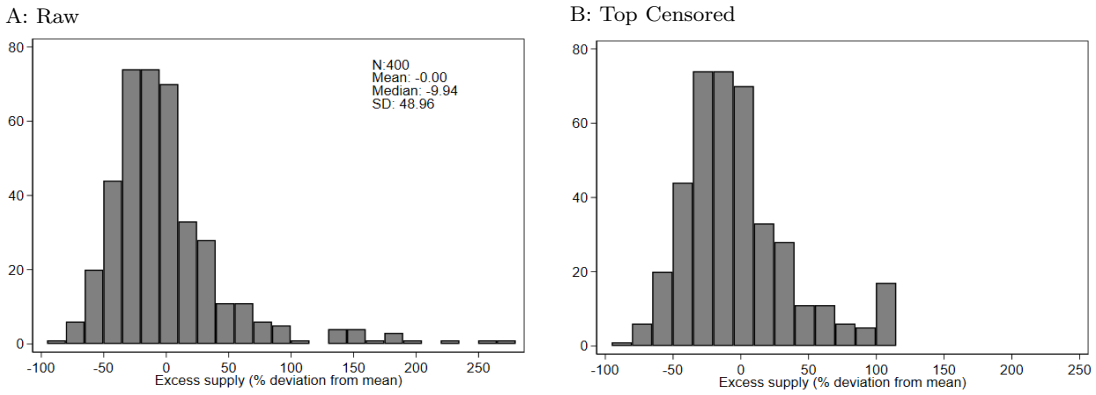
Figure 2. Variation in Therapy Supply within Bedarfsplanungs-Types



Note: The maps visualize the excess supply of psychotherapy within each demand-type in quartiles. Hence, the darker (lighter) districts oversupply (undersupply) psychotherapy holding constant the demand for therapy.

[14] In Figure A.6 we show that mapping between decides of therapy supply and therapy uptake is linear. Given the distribution of excess supply, this implies that the link is weakest in the right tail, where the variance-to-mean ratio is highest.

Figure 3. Distribution of Excess Therapy Supply



Note: Panel A shows the distribution of excess supply across German districts, hence the percentage deviation of the number of therapists per inhabitant from the mean of the demand-type. Panel B shows the same distribution with censoring at 100

4 The Effects of Psychotherapy Supply on Therapy Uptake

4.1 Identification

In the first step, we investigate the effect of psychotherapy supply on its uptake. For that, we compare the mental health care trajectories of individuals in areas with high and low excess therapy supply within the same demand type, hence the same number of psychotherapy licenses per capita. We implement these comparisons through the following regression framework:

$$y_i = \beta \, ExcessSupply_k + \gamma_d + X_i + X_k + \varepsilon_i \tag{3}$$

y_i denotes the health-care uptake of individual i at an arbitrary point in time. The regression includes demand-type fixed effects, γ_d, to restrict the comparisons to those of regions with the same licenses per capita. The regression further includes individual-level and district-level controls (see Table A.1). β denotes the coefficient of interest. It captures how individuals' healthcare uptake responds to increased therapy supply. We scale the measure for excess supply so that β denotes the effect of increasing excess therapy supply by 10 pp from the demand-type's mean. Note that this effect is agnostic to working hours since two therapists sharing a license only work 50 percent more. Taking hours into consideration, β denotes the effect of increasing psychotherapy supply by 5 pp.

To investigate heterogeneous effects of therapy supply, we add to eq. (3) an interaction term of $ExcessSupply_k$ and a binary indicator C_i for whether unit i satisfies

a condition C, such as being female or above median age. The former coefficient of interest, β thus denotes the effect for $C = 0$, while the coefficient of the interaction term poses the effect for $C = 1$. We estimate all models using OLS and cluster the standard errors at the district level.

4.2 Validity

Our empirical strategy builds on the identifying assumption that factors determining excess therapy supply in a district do not affect health-care takeup besides through the usage of psychotherapy. This assumption may be violated for multiple reasons.

First, regions with high excess therapy supply generally provide better health care. This may for example occur if the partialling out in eq. (2) did not fully capture demographic variation in health-care supply. We address this concern thricefold. First, we control for the number of outpatient mental health care providers that are not therapists. Second, we show that excess therapy supply does not predict mental healthcare utilization before 2017. Last, we show that excess therapy supply does not predict the uptake of healthcare unrelated to mental health at any point in time (see Figure A.6).

Second, the assumption was violated if aspiring therapists' demand for shared licenses correlates with patients' demand for health care. This may be the case if therapists behave altruistically and prefer sharing a license in regions of poor mental health. By relying on variation within demand-types, we hold constant demand. In addition, we control for per-capita mental health hospitalizations.[15] Another reason for license and healthcare demand potentially being correlated is therapists' preference to practice in attractive regions. Since licenses are freely traded, the region's attractiveness should be internalized by the price mechanism. In addition, we only compare homogeneous regions due to the demand-type fixed effects and we proxy for a region's attractiveness by controlling for GDP/c and two local amenity indices.

Third, the provided estimates were ill-informative if therapists select into shared licenses based on their productivity. A review by Kegreiss et al. (2023) hints at a positive correlation between working hours of primary care physicians and patient-perceived treatment quality, which appears to be driven by shorter waiting times and better care availability. In the setting at hand, this channel may be reversed, as higher part-time shares correspond to higher therapy supply. Outside the healthcare

[15] Also, aspiring therapists finished at least five years of college plus at least three years of self-funded apprenticeship before having to buy a license. Thus, they have a strong reason to behave economically.

sector, part-time work has been linked to increased productivity (see i.e., Tian et al. 2019). Comparing individuals utilizing therapy after their index discharge in the highest and lowest quartile of therapy supply, we find no differences in their mental health recovery (see Figure A.7) suggesting that therapy provided by shared-license therapists is similarly effective as therapy provided by a full-license therapist.

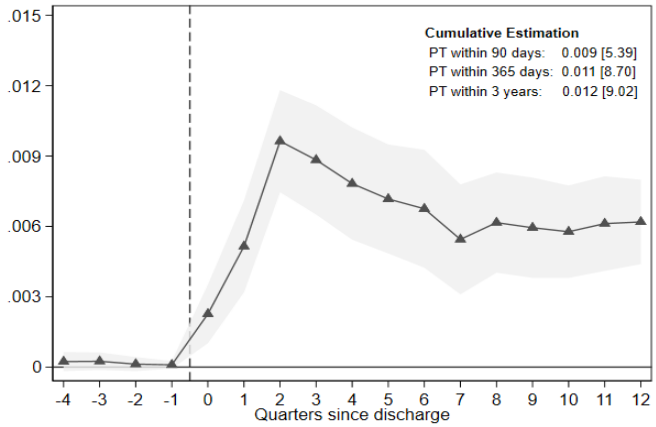
4.3 Results

Figure 2 provides results of the effect of a 10 pp increase in therapy supply (without adjusting for working hours) on being in therapy in a given quarter. While Figure 2 may resemble an event study graph, the markers display repeated estimates of β from eq. (3), with y_i being defined as the uptake of psychotherapy in a respective quarter. Thus, the figure does not show average treatment effects on the treated, but local average treatment effects on compliers. Compliers, in this case, are individuals whose uptake of therapy is sensitive to marginal changes in therapy supply. Similar to event study graphs, time is centered around the index discharge occurring in quarter 0, and estimates in quarters -1 to -4 serve as placebo tests. In addition to the point-wise estimates, the top left shows cumulative estimates in which the outcome is the utilization of therapy within the stated time frame. The brackets contain t-statistics. Figure 2 shows that psychotherapy supply strongly predicts its uptake. For instance, a 10 pp increase in therapy supply increases the share of individuals utilizing therapy by 1 pp. Cumulatively, the supply shock increases the likelihood of starting therapy within a year (three months) by 1.1 (0.9) pp. The figure thereby highlights the dynamics of the effect. Since the healthcare system is congested with median waiting times of 139 days (Germany Federal Parliament 2022), it is plausible that higher supply does not materialize into higher uptake immediately. Thus, compliers are rejected by therapists less frequently, yet also undergo the queue for treatment. These results are insensitive to the coding of excess supply (see Figure A.8). The cumulative effects are homogeneous across age and gender, as well as across diagnoses and severity of the index hospitalization (see Table A.2). Table A.3 contains estimates of the effect on beginning different types of therapy. The additional, supply-induced therapies are weakly more likely ($p = 0.09$) to be CBT than therapies based on Freud, and are significantly more likely to be short and one-to-one therapies ($p = 0.01$ and $p < 0.01$). While the previous results show a large extensive margin response of therapy uptake, the increased supply may also affect the treatment on the intensive margin. For instance, previous research finds significantly negative effects of mental health care supply shortages on waiting time (Prudon 2024; Williams and Bretteville-Jensen

2022). Beyond that, additional therapy supply may also increase the intensity of therapy, which has not been studied so far. To investigate, we estimate eq. (3) only using individuals utilizing therapy in the year after their index discharge. Thus, unlike before, β denotes the intensive margin effect on the combined populations of compliers and always-takers. Since there is no comparison group, we add variables used in the matching as controls.

Table 2 contains the results. Among individuals utilizing therapy, increased therapy supply significantly increases the total number of therapy sessions in the year after the index discharge (Column 1). A 10 pp increase in supply thereby results in 1% more sessions. As such, the intensive margin effect and the extensive margin effect are roughly equivalent in size. The intensive margin effect can be decomposed into two channels. The number of sessions in the year after discharge increases if treatment starts earlier and if the sessions occur at shorter intervals. We test these mechanisms in Columns 2 and 3. While both the treatment delay and the days between therapy sessions shrink, it is mostly the latter that drives the increased treatment intensity.

Figure 4. The Effect of a 10 Percent Increase in Psychotherapy Supply on being in Psychotherapy



Note: The figure is based on the matched sample. The discharge occurs in quarter 0. Each point estimate stems from a separate estimation. The coefficients denote the LATE of a 10% increase in PT supply on being in PT in the respective period. All estimations include demand-type FE, and individual and regional controls. The shaded area denotes 95%−level confidence intervals. The brackets contain t-statistics. The standard errors are clustered at the district level.

Table 2. Intensive Margin Effects of a 10 pp Increase in Psychotherapy Supply

VARIABLES	(1) Number of Sessions	(2) Waiting time (days)	(3) Days between Sessions
Excess Supply (10%)	0.1522***	-0.5576**	-0.0969***
	(0.0425)	(0.2398)	(0.0291)
Observations	15,392	15,392	15,282
Outcome Mean	16.14	127.80	14.06
Outcome Median	14.00	118.00	11.88
Demand Type FE	X	X	X
Individual Controls	X	X	X
Regional Controls	X	X	X

Note: The table contains estimates using only individuals starting psychotherapy within the year after their discharge. The outcomes are the days between discharge and the beginning of therapy (column 1), the number of therapy sessions within the year after discharge, and the number of days between sessions during the time in therapy within the year after discharge. The estimation includes demand-type FE, and individual and regional controls. The standard errors in parentheses are clustered at the district level.

5 The Effects of Psychotherapy Supply on Mental Health

5.1 Results

After showing that psychotherapy supply strongly predicts its uptake, this section aims to study how increased psychotherapy affects individuals' recovery from mental health hospitalization. While the setting may seem suitable for an instrumental variable estimation, it is not. The mental health care uptake is likely a function of being in therapy and therapy intensity. With only a single instrument at hand, the second stage could only contain one of the two. The omitted channel would then violate the exclusion restriction of the instrumented endogenous variable.[16]

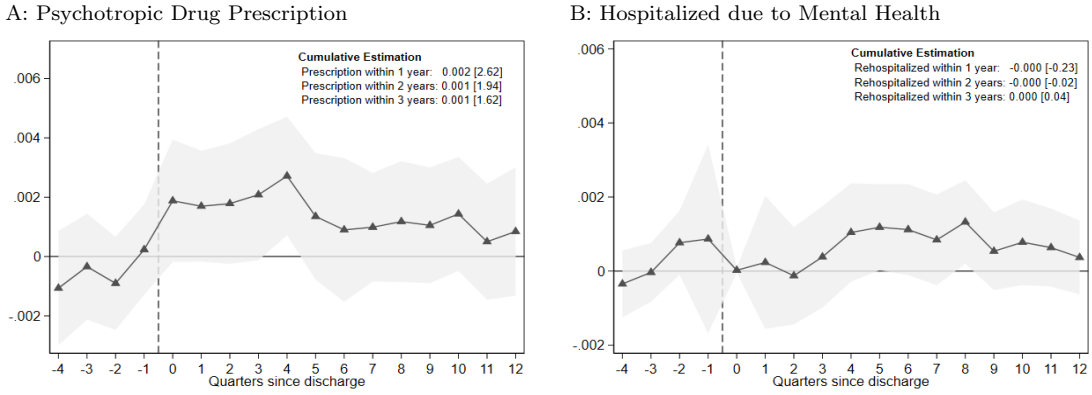
To prevent this issue, we rely on reduced-form estimates in our main specification, yet IV estimates can easily be computed by re-scaling with the first-stage coefficients provided in the previous section. As such, Figure 5 Panel A contains reduced-form estimates of a 10 pp increase in therapy supply on filing a prescription for psychotropic drugs in a given period since index discharge. Coincidentally to the increased uptake

[16]Presume therapy uptake was instrumented and presume both treatment uptake and treatment intensity reduce individuals readmission risk. The IV estimate would be downwards biased (away from zero), since $\hat{\beta}_{IV} = \beta + \frac{Cov(ExcessSupply,\epsilon)}{Cov(ExcessSupply,TherapyUptake)}$, whereas ϵ was the residual of regressing hospital readmission on therapy uptake. In this case $Cov(ExcessSupply, \epsilon) < 0$, since ϵ contains the negative effect of treatment intensity on readmission risk and treatment intensity grows in supply. $\hat{\beta}_{IV}$ would thus exaggerate the true effect, as it does not pose the isolated effect of therapy uptake on health, but the combined effect of treatment uptake under a more vigorous treatment.

of therapy, psychotropic drug adherence increases. Increasing therapy supply by 10 pp thus increases the likelihood of filing a prescription by 0.2% in the first year after the index discharge. Relative to the first stage, this would imply that starting therapy with supply-boosted intensity increases drug usage in the year after the discharge by 18 pp. After the first year, the effects diminish, which may be due to therapy ending, or due to individuals no longer being recommended to use psychotropic drugs to avoid over-treatment.

Panel B shows the effects of psychotherapy supply on readmission risk. Increasing supply by 10 pp reduces the chance of mental health hospitalization neither in the short nor in the long run. The cumulative estimates of re-hospitalization within one two or three years underline the null results being stable over time and precise with t-statistics nearing zero. Analogously, there is no detectable decrease in mental health sick leaves (see Figure A.9), although this result must be taken with a grain of salt for the reasons explained in Section 3.1. Once more, the reduced-form effects are homogeneous across demographic groups, diagnoses, and case severity (see Tables A.4 and A.5), and insensitive to variable coding (see Figure A.8).

Figure 5. The Effect of a 10 pp Increase in Psychotherapy Supply on Mental Healthcare Usage



Note: The figure is based on the matched sample. The discharge occurs in quarter 0. Each point estimate stems from a separate estimation. The coefficients denote the LATE of a 10% increase in PT supply on filing a prescription for psychotropic drugs (left) or having a mental health hospitalization (right) in the respective period. All estimations include demand-type FE, and individual and regional controls. The shaded area denotes 95%−level confidence intervals. The brackets contain t-statistics. The standard errors are clustered at the district level.

5.2 Costs

In addition to the effects on healthcare uptake, policymakers regulating the supply of mental health care may be interested in its cost-effectiveness. While the supply-

induced uptake of therapy naturally invokes costs, it may crowd out the costs of other mental healthcare services. Moreover, inpatient mental healthcare costs provide another proxy for case severity. The previous null-results on readmissions could mask that psychotherapy reduces necessary inpatient treatments to stabilize individuals during mental health emergencies.

Table 3 provides estimates of how a 10 pp increase in therapy supply affects cumulative mental healthcare costs during the three years after the index hospitalization. The additional usage of therapy increases per-patient therapy costs by 64€, or 3% compared to the sample mean. This effect again reflects, that supply not only increases the number of individuals starting a therapy but also the intensity of therapy.[17] The additional uptake of psycho-medication increases costs by 1%, which is statistically insignificant. The null effects on re-hospitalization rates directly translate into no statistically or economically significant changes to hospitalization costs. Additional therapy thus also does not lower the severity of hospital readmissions. Column 4 shows the effect on cumulative costs for outpatient mental health care excluding therapy. Again, the effects are a precise zero, implying that psychotherapy acts as a complement to other outpatient treatments, rather than a substitute. Hence, for the sample at hand, the additional costs for psychotherapy do not self-reimburse to lower uptake of other mental health treatments.

Table 3. The Effect of a 10 pp Increase in Psychotherapy Supply on Mental Health-Care Costs (€)

	(1)	(2)	(3)	(4)
VARIABLES	Psychotherapy	Psychotropic Drugs	Hospitalization	Outpatient Treatment
Excess Supply (10%)	63.50***	7.81	6.93	-0.86
	(8.84)	(4.75)	(80.83)	(3.87)
Observations	30,726	30,726	30,726	30,726
Outcome Mean	2226	759	12364	1678
Matched Sample	X	X	X	X
Demand Type FE	X	X	X	X
Individual Controls	X	X	X	X
Regional Controls	X	X	X	X

Note: The outcomes are the cumulative costs for psychotherapy (column 1), ambulatory visits with a mental health diagnosis excluding psychotherapy (column 2), psychotropic drug prescriptions (column 3), and mental health hospitalizations (column 4) within three years after the initial discharge. The estimation includes demand-type FE, and individual and regional controls. The standard errors in parentheses are clustered at the district level.

[17] Recall that the price for therapy is fixed so that increased costs only reflect changes in quantity.

6 Mechanisms

The absent health benefits of psychotherapy found in this study are surprising, given that many randomized trials find positive effects of psychotherapy. Recent economic contributions by Cronin et al. (2024) and Roth et al. (2024) summarize some of these trials to emphasize the benefits of psychotherapy. Leichsenring et al. (2022), in contrast, provide a large meta-analysis and conclude that many published studies overestimate the benefits of psychotherapy. In this section, we discuss potential explanations for our null effect in light of these contradicting views.

6.1 Local Effects on Compliers

The first underlying mechanism may be selection into psychotherapy based on unobserved treatment success. In Figure 1, we documented that individuals utilizing therapy are highly selective. One dimension of selection may be treatment success. Under scarce supply, therapists could screen out individuals with a high chance of treatment success. Moreover, individuals suspecting being highly susceptible to therapy may be more persistent in demanding therapy. In both cases, always-takers of therapy were characterized by higher treatment success and supply-induced therapy recipients by lower treatment success.

Testing this mechanism is challenging, since neither treatment success or individuals being compliers is not observable at the individual level. In general, therapy recipients differ from the overall sample (see Table 1). However, if treatment success is correlated with individuals' characteristics, this difference itself should vary the more compliers are in the treatment group. To provide suggestive evidence, we build on the intuition that in the lowest supply tercile, the population of therapy recipients comprises every always-taker, and some compliers. In the highest tertile, where therapy uptake is 5 pp higher, the treated population plausibly consists of relatively more compliers. We can then test, whether the difference between therapy recipients and non-recipients changes when compliers switch treatment status due to higher therapy supply.

Column 1 of Table 4 shows that in the lowest supply tercile, individuals utilizing therapy after their discharge are more likely to be female and to be hospitalized with mood disorders, and they had a longer index hospital stay. Column 2 shows these ratios for the highest supply tercile and Column 3 contains t-statistics for testing their difference. The compliers, who only utilize therapy due to the additional supply, do not change the composition of individuals with and without therapy, except for the

prevalence of anxiety disorder among individuals receiving therapy. Thus, under the premise that individuals' treatment effects are correlated with observable characteristics, selection into therapy based on therapy success may pose a secondary role in explaining the null results.

Table 4. Sample Composition in the Lowest and Highest Tercile of Excess Supply

	(1) Tertile 1	(2) Tertile 3	(3) t-stat
Therapy Uptake	.22	.27	11.48
Mean(Therapy=1) - Mean(Therapy=0)			
Female	.18	.19	.38
Age	-3.64	-3.3	.99
Days of 1st hospitalization	9.98	10.12	.19
Substance abuse	-.17	-.17	-.23
Schizophrenia	-.08	-.09	-.97
Mood disorders	.23	.23	-.48
Anxiety disorders	.04	.06	2.41
N	25289	18065	

Note: The upper panel contains the share of individuals utilizing therapy in the year after their index discharge in the lowest and highest tercile of excess therapy supply (Columns 1 and 2). The lower panel shows how individuals with and without therapy in that respective tercile differ in their covariates. Column 3 contains t-statistics of testing for equality of Columns 1 and 2.

6.2 Baseline Mental Health

The second mechanism potentially driving the absent mental-health benefit of therapy may be individuals' low baseline mental health stock. Barker et al. (2022) argue the benefit of psychotherapy lies in preventing mental health deterioration. This prevention may come in too late for individuals having extremely low mental health already. In the setting of this study, we find no benefit of therapy after a mental health hospitalization, thus after an episode of mental health being so low, that individuals were unable to care for themselves, and potentially posed a hazard for them or others. In that sense, the same individuals may have benefited from therapy, had their mental health been better.

Investigating this hypothesis is difficult as by construction, all individuals in our sample experienced at least one mental health hospitalization in 2017. To still provide some evidence, focus on individuals who were not readmitted to the hospital in the two years after their index discharge. We then build on the identification of Oparina et al. (2024) and exploit small variation in the timing of therapy onset. Precisely, we compare individuals starting therapy in quarter τ with individuals starting therapy in $\tau+1$. We implement the comparison following the intuition of a stacked regression (Cengiz et al. 2019). The stack corresponding to quarter τ contains observations from quarter τ of individuals that either start therapy in τ or in $\tau+1$. Individuals utilizing therapy in the past year are excluded to isolate the effect of a newly starting therapy. After stacking the data, we run the following regression model:

$$y_{i\tau} = \delta Therapy_{i\tau} + \theta_{\tau k} + X_i + \varepsilon_{i\tau} \tag{4}$$

$y_{i\tau}$ poses the health outcome of individual i at quarter τ. $\theta_{\tau k}$ denote stack-by-district fixed effects that restrict comparisons to individuals with the same stack and in the same region. Moreover, the regression includes time-invariant controls at the individual level.[18] $Therapy_{i\tau}$ is an indicator equaling 1 for those starting therapy in period τ and 0 for those starting therapy in period $\tau+1$. Its coefficient δ poses the parameter of interest, indicating the association of being in therapy and health.

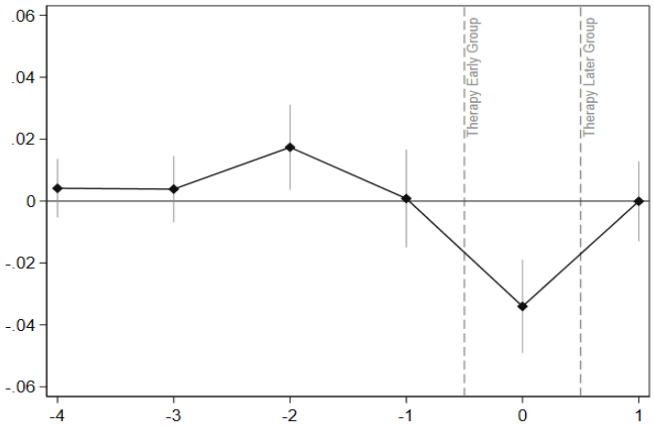
Unlike in the setting of Oparina et al. (2024), we have no randomization of which individuals is treated first. Thus, there is concern that the timing of therapy is linked to lagged health, meaning that a negative mental health shock in the last quarter may trigger therapy today. In this case, we compare individuals receiving therapy in τ to individuals with mechanically low mental health, leading to an overestimation of the effect of therapy in absolute terms. We repeat the estimation using $y_{i\tau+j}$ as outcome of eq. (4). For $j < 0$, δ should be zero if lagged mental health does not strongly predict individuals' current therapy uptake.

Figure 6 provides the results. Among individuals without poor baseline mental health, receiving psychotherapy is associated with a significant 3.5 pp lower chance of mental health hospitalization compared to those receiving therapy in the near future. The figure also shows that receiving therapy in quarter τ vs in $\tau+1$ is not predicted by past health. Moreover, the figure shows that once the control group also receives therapy, the health cap closes again. Thus, among a sample with better mental health endow-

[18] The control variables include age, gender, and length and main diagnosis of the index hospitalization.

ment, we find similarly positive effects of psychotherapy as previous research. This finding reinforces the hypothesis that the effectiveness of psychotherapy negatively corresponds to patients' baseline health.

Figure 6. Association of Therapy and Mental Health Hospitalization among Individuals without recent Hospitalization



Note: This figure shows stacked regression estimates of comparing individuals starting therapy in quarter 0 to those starting therapy in quarter 1 using eq. (4). The sample is limited to individuals without readmission in the two years after their index discharge, and without therapy in the last year. The whiskers denote 95%−level confidence intervals. The standard errors are clustered at the individual level.

7 Conclusion

This paper investigates the effectiveness of psychotherapy in patients' recovery from mental health hospitalization. Using high-quality claims data from Germany, we show that exposure to additional therapy supply largely increases therapy uptake and its intensity. However, psychotherapy does not reduce hospital readmission rates or mental health sick leaves, despite improving psychotropic drug adherence.

We argue that these null results are linked to the underlying population. We provide strong evidence that only among individuals acutely suffering from poor mental health therapy is ineffective. Once individuals recover sufficiently, we find health benefits of psychotherapy similar to related research. Moreover, this paper's empirical design produces local effects for a subset of individuals, whose choice to utilize therapy is supply-sensitive. Past research, in contrast, studies individuals who pre-selected into therapy regardless of supply, i.e., by volunteering for an RCT or by being waitlisted for therapy. While we find no clear signs of effect heterogeneities between these

populations, it cannot be ruled out that individuals self-select into therapy based on private information about their treatment success.

Thus, the results of this paper challenge a widespread belief that psychotherapy is universally beneficial for mental health. Cronin et al. (2024) and Roth et al. (2024), for example, impose this assumption to infer that therapy uptake is sub-optimally low. Our results preach caution when forming beliefs on the benefits of therapy for certain populations, especially for those with severely ill mental health. Further increasing the uptake of therapy may yield limited health advantages. At the same time, therapy and psycho-medication are the only treatment options available, which reflects how unequipped we are in combating the global mental health pandemic.

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Appendix A

Treatment Guidelines for Types of Mental Illness (incomplete)

This section gives a brief overview of the diseases leading the mental health hospitalization, and their recommended treatment:

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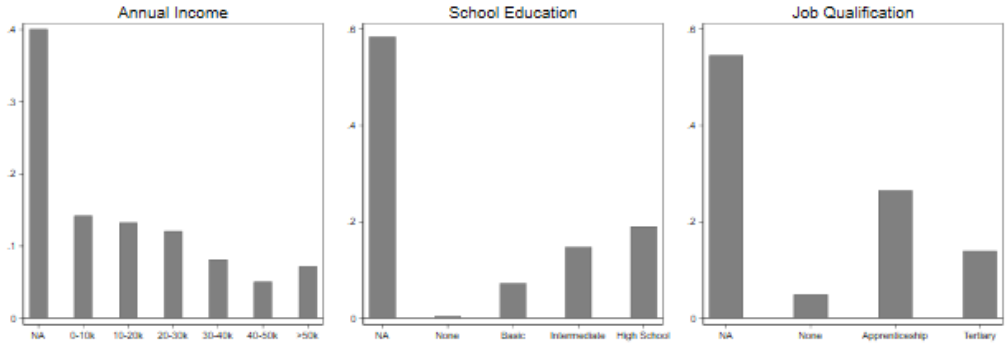
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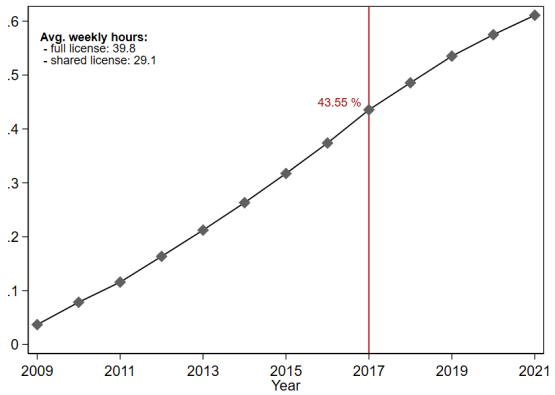
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Appendix Figure A1. Baseline Labor Market Endowment of the Sample



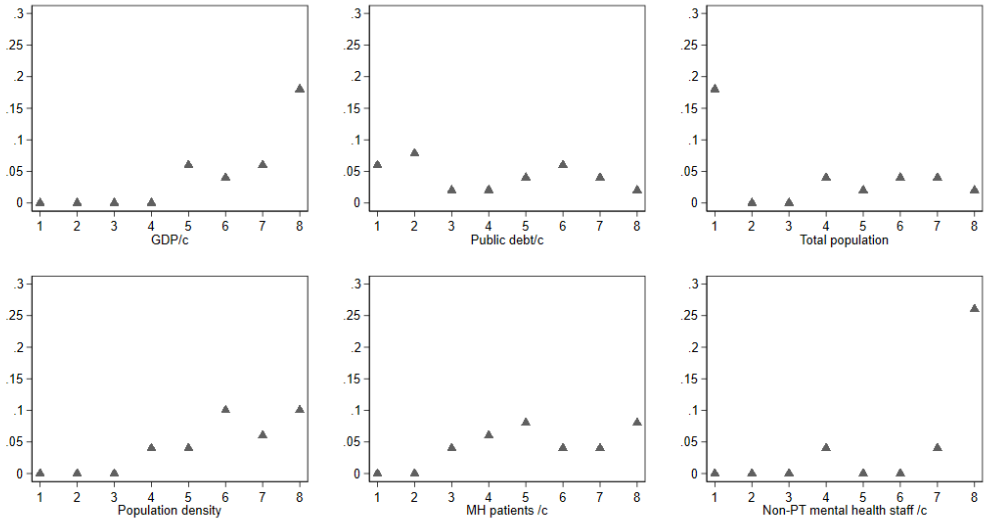
Note: The figure shows the share on individuals in the respective income, highest education and highest qualification cell, using data from 2016.

Appendix Figure A2. Share of Therapist with Shared License



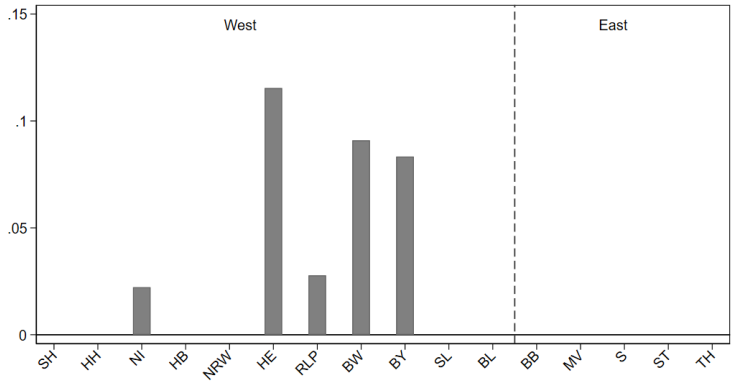
Note: Data from Versorgungsatlas. Working hours from BPtK.

Appendix Figure A3. Outliers in Excess Supply across Regional Covariates



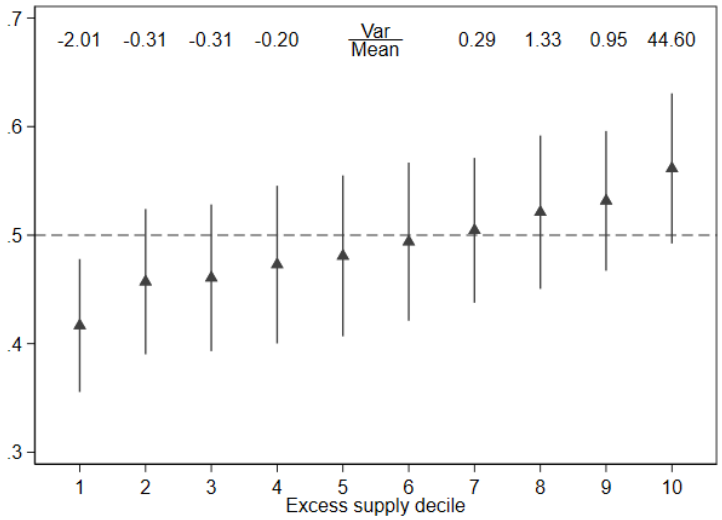
Note: The figures show the share of outliers within octiles of covariates. The sample consists of district level aggregates (N=400). A district is considered an outlier if its excess supply exceeds 100. In total this is the case for 17 districts.

Appendix Figure A4. Share of Outlier Districts by States



Note: The figures show the share of districts classified as outliers per federal state. The sample consists of district level aggregates (N=400). A district is considered an outlier if its excess supply exceeds 100. In total this is the case for 17 districts.

Appendix Figure A5. Excess Therapy Supply and Therapy Uptake within a Year after Discharge



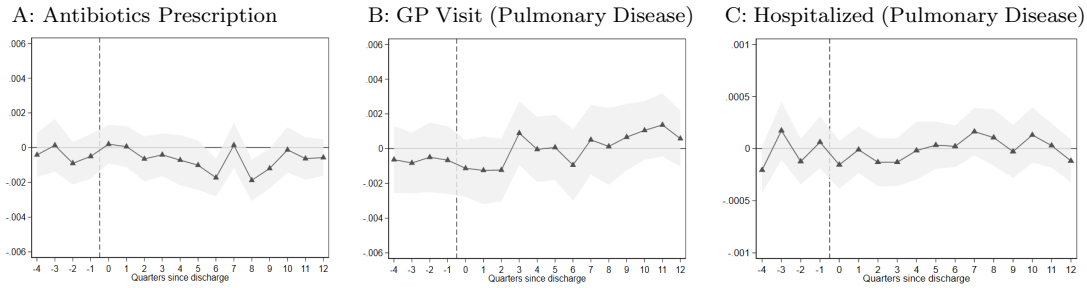
Note: The figure shows the conditionally average therapy uptake within year across deciles of excess supply while controlling for demand-type FE, and individual and regional controls. The whiskers denote 95%−level confidence intervals. The figure is based on the matched sample, hence the average uptake of therapy is 0.5, as denoted by the dashed line. The standard errors are clustered at the district level. The numbers denote the variance mean ratio of excess supply within each decile.

Appendix Table A1. Regional and Individual Level Covariates

	(1)		
	mean	min	max
base_med	.634902	0	1
base_kkh	.162273	0	1
base_amb	5.746859	0	66
q_1	.2698366	0	1
q_2	.2414242	0	1
q_3	.2536939	0	1
q_4	.2350452	0	1
percap_nonth	.0010452	.0004756	.0018866
percap_pat	1.11065	.1108579	2.160269
popd	1204.678	35.9524	4711.062
east	.0963679	0	1
gdpc	41340.58	15738	165521
rank_demographie	147.0116	1	402
rank_sozial	238.9461	1	402

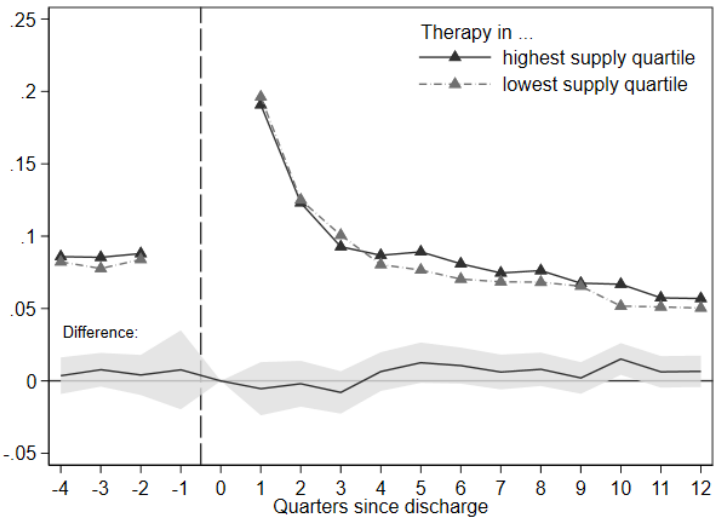
Note: The table lists the control variables using in this paper. The means are produced using the matched sample.

Appendix Figure A6. The Effect of a 10 pp Increase in Psychotherapy Supply on Placebo Outcomes



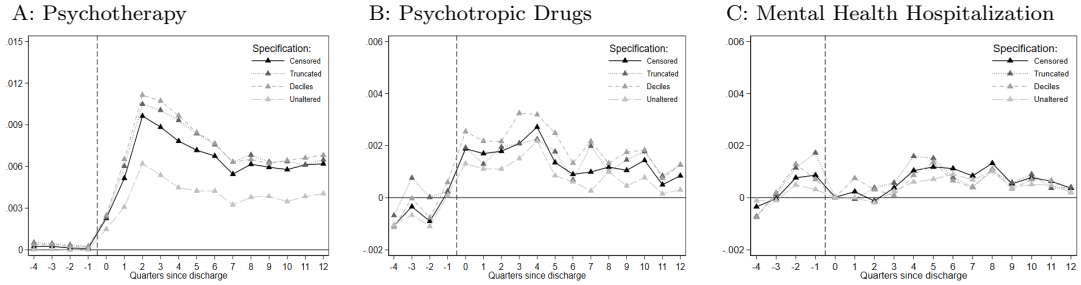
Note: The figure is based on the matched sample. The discharge occurs in quarter 0. Each point estimate stems from a separate estimation. The coefficients denote the LATE of a 10% increase in PT supply on filing a prescription for antibiotics (Panel A), having a GP visit due to a pulmonary disease (Panel B), and being hospitalized due to a pulmonary disease (Panel C) in the respective period. All estimations include demand-type FE, and individual and regional controls. The shaded area denotes 95%−level confidence intervals. The standard errors are clustered at the district level.

Appendix Figure A7. Quarterly Mental Health Hospitalization Rates of Individuals Receiving Therapy in the Lowest and Highest Supply Quartile



Note: The figure shows group means and their difference by event time for individuals starting psychotherapy within the year after their discharge in the highest and lowest quartile of therapy supply (N=7,945). The discharge occurs in quarter 0. The shaded area denotes 95%−level confidence intervals. The standard errors are clustered at the district level.

Appendix Figure A8. Effect Sensitivity to Altering the Outliers in the Excess Supply



Note: The figure replicates the coefficients reported in Figure 4 and Figure 5 using different coding for outliers in the excess supply measure. In the main specification, excess supply is top censored at 100 (black markers). The grey markers provide estimation results when the variable for excess supply is i) truncated at 100, ii) converted into deciles, iii) not changed at all.

Appendix Table A2. Heterogeneous Effect of a 10 pp Increase in Psychotherapy Supply on being in Psychotherapy

	(1)	(2)	(3)	(4)
VARIABLES	Female	Age $\geq$ *median*	Depression	Severity $\geq$ *median*
Excess Supply (%)	0.0114***	0.0107***	0.0131***	0.0124***
	(0.0016)	(0.0016)	(0.0017)	(0.0015)
Interaction	0.0011	0.0029	-0.0015	-0.0006
	(0.0018)	(0.0020)	(0.0016)	(0.0015)
Observations	30,742	30,742	30,742	30,742
Matched Sample	X	X	X	X
Type FE	X	X	X	X
Quarter FE	X	X	X	X
Regional Controls	X	X	X	X

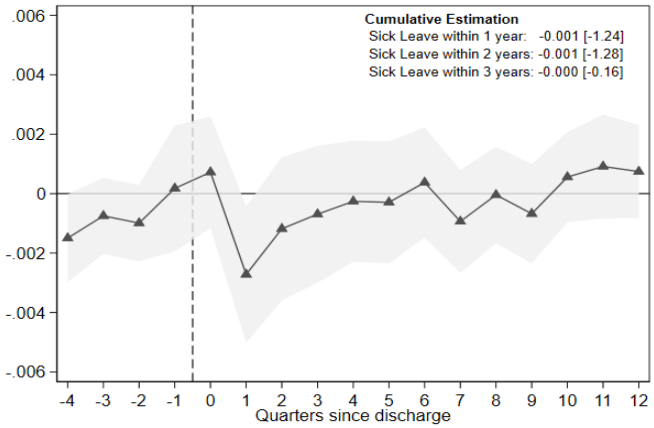
Note: The figure is based on the matched sample. The outcome is an indicator on receiving psychotherapy within the year after the initial discharge. The interaction term poses the differential effect of a 10 percent increase in PT supply for the group stated in the column header. Severity is measured as the length of initial hospitalization demeaned within diagnosis. The estimation includes demand-type FE, and individual and regional controls. The standard errors are clustered at the district level.

Appendix Table A3. The Effect of a 10 pp Increase in Psychotherapy Supply on being in Specific Types of Psychotherapy

VARIABLES	(1) CBT	(2) Freud	(3) Long	(4) Short	(5) One-to-one	(6) Group
Excess Supply (10%)	0.0077***	0.0037***	0.0037***	0.0072***	0.0115***	-0.0005
	(0.0014)	(0.0013)	(0.0008)	(0.0011)	(0.0012)	(0.0004)
Observations	30,726	30,726	30,726	30,726	30,726	30,726
Mean Outcome	0.282	0.223	0.135	0.365	0.474	0.026
SURE Pval	0.090	0.090	0.014	0.014	0.000	0.000
Matched Sample	X	X	X	X	X	X
Demand Type FE	X	X	X	X	X	X
Individual Controls	X	X	X	X	X	X
Regional Controls	X	X	X	X	X	X

Note: The outcome is an indicator on beginning a cognitive behavioral therapy vs a therapy based of Freud (Columns 1 and 2), a short vs a long therapy (columns 3 and 4), and a one-to-one vs a group therapy within the year after discharge. The table also provides p-values of testing whether the coefficients in Columns 1 and 2, 3 and 4, and 5 and 6 are equal using seemingly unrelated regression. The estimation includes demand-type FE, and individual and regional controls. The standard errors in parentheses are clustered at the district level.

Appendix Figure A9. The Effect of a 10 pp Increase in Psychotherapy Supply on Having a Mental Health Sick Leave



Note: The figure is based on the matched sample. The discharge occurs in quarter 0. Each point estimate stems from a separate estimation. The coefficients denote the LATE of a 10% increase in PT supply on having a mental health sick leave in the respective period. All estimations include demand-type FE, and individual and regional controls. The shaded area denotes 95%−level confidence intervals. The brackets contain t-statistics. The standard errors are clustered at the district level.

Appendix Table A4. Heterogeneous Effects: Psychotropic Drug Prescription Within One Year After Discharge

VARIABLES	(1) Female	(2) Age $\geq$ *median*	(3) Depression	(4) Severity $\geq$ *median*
Excess Supply (10%)	0.002	0.003***	0.004***	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
Interaction	0.000	-0.002	-0.002	-0.002
	(0.001)	(0.002)	(0.002)	(0.001)
Observations	30,584	30,584	30,584	30,584
Outcome Mean	0.730	0.730	0.730	0.730
Matched Sample	X	X	X	X
Demand Type FE	X	X	X	X
Individual Controls	X	X	X	X
Regional Controls	X	X	X	X

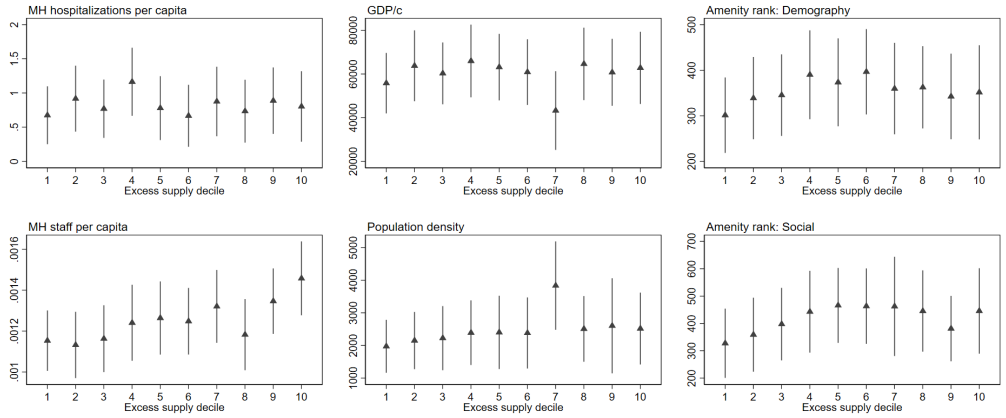
Note: The figure is based on the matched sample. The outcome is an indicator on having filed a prescription for psychotropic drugs within the year after the initial discharge. The interaction term poses the differential effect of a 10 percent increase in PT supply for the group stated in the column header. Severity is measured as the length of initial hospitalization demeaned within diagnosis. The estimation includes demand-type FE, and individual and regional controls. The standard errors are clustered at the district level.

Appendix Table A5. Heterogeneous Effects: Mental Health Hospitalization Within Three Years

VARIABLES	(1) Female	(2) Age $\geq$ *median*	(3) Depression	(4) Severity $\geq$ *median*
Excess Supply (10%)	0.002	-0.001	-0.000	-0.000
	(0.002)	(0.001)	(0.002)	(0.001)
Interaction	-0.003*	0.002	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Observations	30,726	30,726	30,726	30,726
Outcome Mean	0.427	0.427	0.427	0.427
Matched Sample	X	X	X	X
Demand Type FE	X	X	X	X
Individual Controls	X	X	X	X
Regional Controls	X	X	X	X

Note: The figure is based on the matched sample. The outcome is an indicator on having a mental health hospitalization within three years after the initial discharge. The interaction term poses the differential effect of a 10 percent increase in PT supply for the group stated in the column header. Severity is measured as the length of initial hospitalization demeaned within diagnosis. The estimation includes demand-type FE, and individual and regional controls. The standard errors are clustered at the district level.

Appendix Figure A10. Regional Covariate Balance accross Deciles of Excess Supply



Note: The figure shows conditional means of regional covariates across deciles of excess supply while controlling for demand-type FE, and individual and regional controls. The whiskers denote 95%−level confidence intervals. The figure is based on the matched sample. The standard errors are clustered at the district level. The whiskers denote 95%−level confidence intervals.