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The effect of local growth in antidepressant consumption on mental health outcomes

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– Draft Version –

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Abstract

Despite growing skepticism regarding the efficacy of antidepressants, global consumption is increasing at an unprecedented path with unknown implications for society. We estimate the causal effect of this increase on mental health outcomes using an IV strategy that exploits detailed drug sales data from Switzerland between 2002 and 2014. Our instrument, a modified version of the popular shift-share instrument, relies on the national growth in antidepressant sales for pharmaceutical companies (the shift) - mainly due to product innovation - and assigns it locally using regional non-antidepressant market shares. Our estimates show that an increase in antidepressants sales does not significantly affect suicide rates but cause an increase of hospital admissions for mental disorder and for depression. The causal effects prove to be resistant to several robustness checks.

Keywords: Depression; antidepressant treatment; suicides; mental health
JEL codes: I12, I18

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1. Introduction

Antidepressants are among the most widely prescribed drugs. Their consumption has been growing at a steady pace and has doubled over the last decade (McCarthy, 2013). Despite this substantial increase in antidepressant use, prescription guidelines have not been substantially altered in recent years (Anderson et al., 2000, 2008), while studies suggests that prescription thresholds have been lowered and antidepressants are increasingly prescribed off-label (Moore et al., 2009). Consequently, there is rising concern over the efficacy of these drugs and the potential implications for society. Although evidence on efficacy is mostly grounded on randomized controlled trials (RCT), several meta-studies have questioned the results (Jakobsen et al., 2017; Cipriani et al., 2016; Kirsch et al., 2008; Healy and Whitaker, 2003). Critics point to methodological issues, such as the short duration of the RCT, small sample size, under-reporting of adverse events during the trials, blind-breaking and the use of a placebo washout period. This study intends to contribute to the ongoing debate on antidepressant efficacy with a causal estimate of the effect of antidepressant drug sales on several mental health outcomes.

Several recent meta-studies shed light on the efficacy of antidepressant treatment and the occurrence of adverse events. Awareness for adverse events was spurred in October 2004 when the US Food and Drug Administration (FDA) issued a black box warning for all antidepressants (Busch et al., 2014). This announcement motivated several authors to analyze the drug trial data submitted to the FDA to obtain US market access. The results of these (and other) studies suggest that baseline depression severity matters for antidepressant efficacy, while clinical efficacy is only significant for the most severely depressed, and benefits are minimal or non-existent in patients with mild or moderate

symptoms of depression (Fournier et al., 2010; Stone et al., 2009; Kirsch et al., 2008). Antidepressants appear to have particularly adverse effects for children, adolescents and the elderly. Indeed, their use is associated with a modest increase in suicide risk among pediatric patients, and with several adverse health outcomes among the elderly (Cipriani et al., 2016; Coupland et al., 2011; Stone et al., 2009; Hammad et al., 2006).

According to the 2008 British Association for Psychopharmacology guidelines, antidepressant treatment is recommended only in moderate and severe cases of depression, and possibly in combination with some form of psychotherapy (Anderson et al., 2008).[1] Evidence suggests that the prescription threshold shifted towards milder forms of depression, thanks to the introduction of Selective Serotonin Reuptake Inhibitors (SSRI) (Moore et al., 2009). At the time of their introduction in the '90s, SSRI were hailed as having a comparative advantage over old classes of antidepressants , such as Tricyclic antidepressants (TCA), especially in terms of lower side-effects (Lane et al., 1995). Whether this was because TCA were particularly harmful or because SSRI were indeed very safe, has not been established in the literature yet (Cohen et al., 2000; Sharma et al., 2016; Jakobsen et al., 2017).

There is an extensive medical literature on the spatial correlation between antidepressant consumption and suicides with often mixed results (e.g., Gibbons et al., 2005). As far as we know, the only paper that provides evidence of a negative causal relationship between antidepressant consumption and suicides is Ludwig et al. (2009). Using data from 1980 to 2000, the authors exploit the differential introduction of SSRI drugs across countries and find that an increase of SSRI sales by one pill per capita reduces suicides by 5%.

[1] The most recent guidelines from the same association are from 2015 and, therefore, are not relevant for the period under study. Nonetheless, these guidelines (Cleare et al., 2015) provide the same recommendations.

Although insightful, this result is no longer applicable to the current level of antidepressant consumption because, nowadays, the large part of antidepressants consumed are SSRI, and the marginal patient treated with antidepressant drugs likely suffers from a milder form of depression as compared to the marginal patient at the beginning of the '80s when SSRI were introduced. Note also that antidepressant consumption in the US has increased by 400% between the early nineties and the beginning of this century (Pratt et al., 2011), and similar trends are observed in most other developed countries.

This paper provides new insights into the consequences of the surge in antidepressant consumption. To achieve this aim, we exploit small area variations in antidepressant consumption using sales data for Switzerland from 2002 to 2014. As illustrated by the maps in Figure 1, antidepressant consumption shows considerable variation over both time and space. We intend to exploit this variation to establish a causal link between antidepressant sales and mental health outcomes. Our study contributes to the understanding of the efficacy of antidepressant use in two main ways. The first contribution of this paper lies in the investigation of health outcomes, such as hospitalization for mental health conditions and depression, in addition to suicides that are usually characterized by a very-low event probability. Ideally, we would also like to assess the effect of antidepressant use on depression prevalence, but unfortunately, a reliable measure of depression prevalence is not available for Switzerland.

The second contribution of this paper relates to the empirical strategy used to enhance the causal interpretation of our results. We address the endogeneity concern that arises in ecological studies by utilizing an instrumental variable (IV) approach. Our instrument is inspired by the popular shift-share approach (Bartik, 1991) but substantially diverges regarding its implementation. Similar to the standard shift-share instrument, it is es-

sentially a weighted average of national manufacturer (pharmaceutical company) growth rates (the shifts), but the weights of our instrumental variable depend on the manufacturer market shares for non-antidepressant drugs in the base year (the shares). The variation in the shares comes from historically grown differences in market power between manufacturers in different Swiss regions, while the change in the growth rates (net of year fixed effects) mainly derives from the introduction of new products in the market (as reported in Figure 2). The nature of the instrument allows us to alleviate concerns regarding the correlation between the initial shares and health conditions of the region because we exploit the plausibly exogenous variation in the market power of pharmaceutical companies in the non-antidepressant market.

Using a two-stage least squares fixed effects model, we find that antidepressant consumption does not affect suicides. However, an increase in consumption of one defined daily dose per 1,000 inhabitants (roughly 3% of 2003 sales) increases hospital admissions for mental disorders by 2% and hospitalization for depression by more than 7%. These results prove to be robust to the enlargement of the time gap between the base year (in which we calculate the shares) and the years for which we estimate the effect. Moreover, in a series of placebo estimates aimed to test the exogeneity of our instrument indirectly, we do not find any evidence of relevant correlations between the increase in antidepressant sales induced by our instrument and hospital admissions for diseases that should not be affected by the increase in antidepressant use. The only exception is cancer, but the correlation is negative (meaning fewer hospitalizations for cancer) and disappears as we increase the time lag between the base year and the years for which we estimate the effect.

The remainder of this paper is organized as follows. In the next section, we introduce the Swiss institutional setting in which we conduct our analysis. In Section 3, we describe the

data used for the analysis and the data aggregation process. In Section 4, we discuss our empirical strategy while in Section 5 we present our results. Finally, Section 6 concludes.

2. Institutional setting

We use data for Switzerland to study the effects of antidepressant use on mental health outcomes. Switzerland is a confederation of 26 cantons with considerable autonomy in the organization and the provision of health care services. The supply of mental health care is a cantonal responsibility, though the federal state organizes some of the fundamental financial aspects (Biller-Andorno and Zeltner, 2015). Private health insurance is mandatory and regulated by federal laws. The insurance plan covers an extensive list of prescription drugs and, therefore, Swiss consumers face almost no costs when using antidepressants. A consumer can opt for a Health Maintenance Organization (HMO) type of health insurance or a general practitioner (GP) scheme, which allows the consumer to reduce the insurance premium. Cantonal authorities provide subsidies for those consumers facing financial hardship. The minimum annual deductible amounts to 300 CHF (1 CHF $\approx$ 1 US \$), but the consumer can choose a higher deductible, up to 2,500 CHF, against a decrease in the insurance premium. After the deductible is exhausted, the consumer contributes by 10% to all health care expenses, up to a stop-loss amount of 700 CHF. Moreover, the federal government introduced a 20% co-insurance rate for off-patent brand name medications in 2006.

Individuals who suffer from mental disorders generally opt for the minimum deductible. Moreover, the deductible is quickly exhausted by physician visits and psychotherapy con-

sultations.[2] To provide an idea of the potential costs of antidepressant treatment for a patient, the price per defined daily dose for the most prescribed (brand name) drug in Switzerland (Cipralex 10mg) is about 1.32 CHF, or 480 CHF a year. According to the drug list, this drug has a 20% co-insurance rate. Therefore, a patient treated with this drug pays at most 336 CHF a year out of pocket. No antidepressant is available "over the counter" since all antidepressants without exception are prescription drugs. Lastly, Masiero et al. (2018) find that antidepressant consumption in Switzerland is associated with physician density, suggesting that supplies may induce demand at least to some extent. All in all, consumers determine the demand for antidepressant drugs only to a small degree.

The Federal Office of Public Health (FOPH) sets prices for prescription drugs in Switzerland. After a drug has been granted access to the Swiss market by the federal authority (Swissmedic), the FOPH decides whether to include the drug in the list for reimbursement (Spezialitätenlist - SL) upon evaluating its efficacy. Antidepressants are relatively expensive in Switzerland, and the price difference between brand names and generic drugs is not very large. Generic drugs are at least 50% more costly than in other European countries.[3] These market characteristics suggest that drug manufacturers in Switzerland are likely to compete on quantity rather than in prices. Since only physicians can prescribe antidepressants and federal laws prohibit direct-to-consumer advertising for prescription drugs, manufacturers can only influence their sales through physician detailing.

[2] According to the Swiss tariff system for out-patient medical services (TARMED), the cost for a psychiatric consultation amounts to 11.20 CHF per five minutes. A psychotherapeutic consultation or a GP consultation amount to 10.42 CHF per five minutes. For instance, with only two hours of treatment per month, the deductible is already exhausted in a couple of months. For the remaining part of the year, the patient only pays the co-insurance rate.

[3] See the recent press release by the Swiss health insurance association (Santésuisse, 2017) on the international comparison between generic drug prices in Switzerland and prices in Belgium, Denmark, Germany, Finland, France, Great Britain, the Netherlands, Austria, and Sweden.

The prevalence rate of mental health problems in Switzerland is similar to other developed countries (Schuler and Burla, 2012). Severe cases can be treated both in private and public hospitals. Hospitals charge a daily fee which is decreasing with the length of stay (Schneeberger and Schwartz, 2018). Cantons and health insurance provider share the costs of psychiatric hospital stays. Although hospital admissions for mental health disorders have increased over time, the number of psychiatric hospital beds per capita has declined, and a growing number of patients is treated in outpatient settings. Similar trends are observable for other European countries (Priebe et al., 2008). The fees for the services provided by outpatient departments/clinics are standardized in the TARMED tariff system to avoid differential treatment of patients with different insurance plans.

3. Data

We exploit two primary datasets on antidepressant sales and mental health outcomes for Switzerland covering the period from 2002 to 2014. The data is aggregated at the small area level (SMR - spatial mobility region) which divide Switzerland into 106 SMR regions with each of them accounting for approximately 45,000 individuals. An SMR is a statistical subdivision of Switzerland based on economic activity around an agglomeration hub. As such, each region represents a local labor market or commuting zone.

The level of disaggregation allows us to account for population characteristics and neglect possible consumption spillovers across regions. Indeed, people living in one region are highly unlikely to work in a neighboring region and, therefore, to shop for antidepressants outside the SMR of residence. Thus, measuring antidepressant consumption at the level of commuting zones represents an effective way to deal with the potential for measurement error. Nonetheless, an additional source of measurement error may arise from the use of

wholesale data (from the manufacturer to the pharmacy/drugstore) since we measure what the pharmacist stocks rather than sales to the final consumer. Although our observations of final consumption are on average correct, we could overestimate antidepressant use in some cases.

To account for confounding factors, we supplement our primary datasets on antidepressant sales and mental health outcomes with data on essential covariates for each region and year. These variables are the distribution of the population across gender and age, the share of German-speaking people and the share of foreigners, and the average municipal unemployment rate. Lastly, we obtained access to anonymized data by the Swiss Medical Association (FMH), which allowed us to calculate the share of antidepressant prescribing specialists (Neurologists and Psychiatrists) and GPs per 10,000 inhabitants.

3.1 Antidepressant sales and mental health outcomes

We obtained data on antidepressant sales from IMS Health Switzerland. This dataset contains annual antidepressant sales at the product level by pharmaceutical sales region (237 regions) from 2002 to 2014. This level of aggregation includes at least five pharmacies to avoid identification of specific retailers. The level of detail allows us to calculate the consumption of each antidepressant product in defined daily doses (DDD) per 1,000 inhabitants per year based on information from the WHO dataset on daily doses by active ingredient. In particular, we consider sales data for the following Anatomical Therapeutic Chemical classes (ATC): N06A4 (Selective Serotonin Reuptake Inhibitors - SSRI), N06A5 (Serotonin and Norepinephrine Reuptake Inhibitors - SNRI), and N06A9 (Other antidepressants, including Tricyclic antidepressants - TCA) (see Table A.1 for the active ingredients included in each classes). Although herbal medicines (class N06A2) enjoy a high level of acceptance in the Swiss population, we exclude them from our analysis

since we can not define the daily dose for this class of antidepressants. We also use an accessory dataset with annual sales for the universe of all other drugs aggregated at the manufacturer level by pharmaceutical sales region for the period from 2002 to 2014.[4]

We obtained individual-level data on mental health outcomes from the Federal Statistical Office (FSO). The most detailed geographical aggregation at which hospital admission data are available for Switzerland is the MedStat region level. The MedStat regions are a geographical concept used by the FSO to anonymize individual-level hospital admission data.[5] We use a population-weighted matching procedure to reassign data aggregated at the MedStat level to the SMR level, and from the pharmaceutical sales region to the SMR level. The matching method allows us to build a final dataset with comparable spatial data on both antidepressant consumption and mental health outcomes. We express mental health outcomes in terms of annual prevalence per 10,000 inhabitants by SMR throughout our analysis.

We consider three different mental health outcomes in our analysis. To capture the impact on suicide, we create a measure of completed suicides and hospital admissions for suicide attempts (Intentional Self-harm - X60-X84). We also account for hospital admissions for depression (depressive episode - F32, and Recurrent Depressive Disorder - F33), and hospitalizations for other mental health conditions (Chapter V).[6] Data on mortality are

[4] A negligible number of drugs with a retail price greater than $5,000$ CHF is also not included in the analysis.

[5] An advantage of these data is that the 604 MedStat regions are homogenous regarding the population size, with each of them containing about 12,000 people. It is important to note that the spatial definition was updated in 2008 to account for population growth. Based on postal codes for 2007, the old MedStat regions were split up or combined to form new MedStat regions. Therefore, it is impossible to study hospital admissions over the structural break without reassigning the data from the new to the old definition of MedStat region. We accomplish this task by matching postal codes underlying the MedStat regions over the structural break. We obtained detailed information on the general population at the postal code level for 2010 from the FSO. We use this information to create weights and recode the location information to obtain a match between the new and the old definition. We then reassign the morbidity data over the structural break using population weights.

[6] All disease codes refer to the International Statistical Classification of Diseases and Related Health Problems, 10th Revision, of the WHO.

from the official Swiss mortality statistics, and hospitalization data are from the Swiss hospital statistics.

3.2 Descriptive evidence

We summarize the main variables used in our analysis in Table 1. The average antidepressant consumption across SMR regions and for the whole period under study is more than 40 DDD per 1'000 inhabitants, with an increase of almost twenty DDD over the last decade. The spatial and temporal variation in antidepressant consumption are illustrated in Figure 1. We observe a sharp increase over time in all regions. However, most of the variation is across small areas, and another important source of variation comes from the introduction of new products. Figure 2 shows the number of newly introduced antidepressants per year.[7] We will discuss the use of this source of variation to construct our instrument for antidepressant consumption in Section 4. Interestingly, the consumption is mostly concentrated in South-Western regions in 2003, while there is no clear concentration in any region in 2014. Hence, the increase in consumption over time characterizes a catching-up process with the strongest increase in the North-Eastern regions.

A similar pattern is observable for mental health outcomes in Figure 3. In particular, hospital admissions for mental disorders and depression show a significant increase over time. Subfigures (a) and (c) highlight the concentration of mental health disorders and depression in South-Western regions in 2003. The prevalence of both mental disorders and depression appear to increase in the North-Eastern areas compared to 2014 according to subfigures (b) and (d). The variation in suicide rates provides a far more complex picture, probably due to the rare-event nature of suicides. The comparison of subfigures (e) and

[7] Additional details (manufacturer, active ingredient and year of introduction) for new brand name products and generic drugs are provided respectively in Table A.2 and Table A.3.

(f) does not seem to suggest a clear spatial or temporal pattern, although we see evidence for an increasing number of cases in some Eastern regions.

4. Empirical strategy

Following previous literature on the effect of antidepressant sales or consumption on suicides (e.g. Ludwig et al., 2009), our estimates of the effect of antidepressant sales on mental health outcomes relies on the following empirical model:

$$y_{rt} = \alpha + \beta AD_{rt} + \gamma X_{rt} + \vartheta_r + \vartheta_t + \epsilon_{rt}, \tag{1}$$

where y_{rt} is the natural log of the mental health outcome (number of hospital admissions for mental health problems, depression or number of suicides rates per 1'000 inhabitants in year t)[8] in region r at time t; AD_{rt} represents antidepressants sales (expressed in DDD per 1'000 inhabitants in year t) in the same region at the same time; X_{rt} is a vector of controls, including demographics (the age distribution of the population, the share of females, the share of German speakers, and the share of foreigners), the level of unemployment in a region, and the density of antidepressant prescribing physicians; ϑ_r are region fixed effects, ϑ_t are time fixed effects, and ϵ_{rt} is an idiosyncratic error term. We use the natural log of mental health outcomes to approximate a normal distribution for our data, for ease of interpretation, and because of the convention in the literature.[9] As a robustness check, we also estimate (1) assuming a data generating process that mimics the Poisson distribution.

We use the fixed effects (FE) estimator as our benchmark model to estimate Equation

[8] Some concerns might arise having the population on both the left and right end side of our regression. However, results are almost identical if we use the simple log count of our outcome variables.

[9] We take care of zeros for suicides by adding a small constant to each outcome.

(1). Given the substantial scale differences between small areas (we move from almost half a million inhabitants in Zurich to less than 10,000 in Appenzell-Innerhoden), we weight our estimates for the population. This weighting approach allows us to correct for heteroskedasticity in the error term (Solon et al., 2015), and alleviate the measurement error problem. Indeed, more populated areas show a higher signal-to-noise ratio, which is an issue, especially when dealing with a low-frequency outcome such as suicides.[10]

Antidepressant consumption is endogenous to the conditions that also influence mental health outcomes. The inclusion of region fixed effects allows us to remove all time-invariant unobservables, but this does not allow us to get rid of all the endogeneity concerns. Several omitted time-varying factors may still bias our estimates. The latent health status of the population may affect both the use of antidepressants and the prevalence of mental health disorders in a region causing an upward bias of our FE estimates. Moreover, there have been attempts to create awareness of depression and decrease stigma in the general population and among health care practitioners. We would expect such policy interventions to have a positive effect on antidepressant sales since they encourage uptake of antidepressant treatment, and possibly a negative impact on mental health outcomes. Therefore, the bias in the estimates could be either upward or downward, depending on which of the two effects is stronger.

Controlling for these factors is difficult because, for example, a reliable measure of depression prevalence is not available and we do not have enough power to measure the effect of cantonal depression awareness campaigns.[11] Moreover, the health status of the popu-

[10] Comparing Zurich (a densely populated city) and Appenzell Innerhoden (a scarcely populated rural area), we observe a large variability in the mental health outcomes (see Figure A.1).

[11] The "Alliance against Depression" is active in several (German-speaking) Swiss cantons and creates awareness for depression in the general population, and among physicians, teachers, etc. However, the program's scope, length and stakeholders are up to the discretion of the cantons.

lation is an outcome as well (what Angrist and Pischke (2008) define as "bad controls"). To account for this issue, we rely on an instrumental variables strategy to estimates the impact of antidepressant sales on mental health outcomes.

4.1 Instrumental variable approach

The instrument for our identification strategy is an adaptation of the traditional shift-share instrument (Bartik, 1991) where national levels of antidepressant sales for each manufactures are assigned to regions using the supply-driven increase in antidepressant sales. Our instrument diverges from the standard shift-share approach in two important ways. First, we use regional market shares, rather than regional sales relative to national sales, to calculate the regional shares. Indeed, the use of regional sales to calculate the regional shares would be endogenous since most manufacturers are likely to sell more in areas where the mental health conditions of the population are poor. The use of market shares allows us to overcome this problem since we consider the sales of each manufacturer relative to its competitors. Second, the market shares are computed using non-antidepressant drugs sales. Therefore, we use a different market to exploit the market power of each manufacturer in a region and to avoid concerns regarding the potential endogeneity of our shares. We also normalize the final shares for each manufacturer against the sum of its regional market shares (such that the share takes a value between zero and one). Therefore, the weighted average of these shares and the national growth in annual antidepressant sales per manufacturer (the shifts) is our instrument (Goldsmith-Pinkham et al., 2018; Jaeger et al., 2018). In practice, we exploit the fact that manufacturers tend to sell more in areas where they have higher market power (relative to their competitors). Hence, we allocate the annual sales of antidepressant drugs of each manufacturer using its regional market share for non-antidepressant drugs.

To have predict power, we also need variation between manufacturers in their national growth rate (net of the overall yearly change in AD sales captured by the time fixed effects). As reported in Figure 2, the introduction of several new products in the market, some covered by a new patent (brand name introduction), and some others as new generic drugs (first or secondary introduction) provides this variation.

The underlying assumption of our IV strategy is that a manufacturer's market share in the non-antidepressant market is exogenous to mental health outcomes, and does not affect the mental health outcomes of the population (exclusion restriction) directly. This assumption is violated if pharmaceutical companies, through their market power in the non-antidepressant market, were able to influence hospital admissions for severe mental health problems, which is hard to believe.

Because of data restrictions, our main estimates are obtained using 2002 as a base year to construct the shares, while analyzing the relationship between antidepressant sales and mental health outcomes for data from 2003 to 2014. Although our shift shares are different from those commonly employed in the literature, some concerns might still arise because there is no time gap between the base year and the years for which we estimate the effect of antidepressant sales on mental health outcomes. For this reason, we substantiate the validity our instrument by re-estimating the model using increasing time gaps between our base year (2002) and the years used for the estimation (using incrementally fewer data in steps of one year).[12] The robustness of our findings to the increasing time gap confirms our main results.

More formally, our instrument is constructed as follows. Let the annual national stock of

[12] A time gap of one year implies that we are using data from 2004 to 2014; a time gap of two years implies that we are using data from 2005 to 2014, and so on.

antidepressant for each manufacturer be represented by $AD_{mt} = \sum_r AD_{mrt}$, where AD_{mrt} represents the antidepressant sales for manufacturer m in region r at time t. The stock is used to calculate the shifts. The shares instead are calculated as follows:

$$\widetilde{S}_{mr2002} = \frac{MS_{mr2002}}{\sum_r MS_{mr2002}}, \tag{2}$$

where $\text{MS}_{mr2002} = \dfrac{v_{mr2002}}{\sum_m v_{mr2002}}$ is the market share from wholesales of non-antidepressants (v_{mrt}) for manufacturer m, in region r, in the base year 2002, with $0 < \widetilde{S}_{mr,2002} < 1$[13]. This allows us to redistribute AD_{mt} as follows:

$$\widetilde{AD}_{mrt} = \widetilde{S}_{mrt} \times AD_{mt}, \tag{3}$$

where the regional variation in $\widetilde{AD}_{mrt}$ comes from variation in manufacturer non-antidepressant market shares in the base year, and temporal variation from national manufacturer growth rates. Finally, we sum $\widetilde{AD}_{mrt}$ over m to obtain our instrument as follows:

$$\widetilde{AD}_{rt} = \sum_m \widetilde{AD}_{mrt}. \tag{4}$$

We can now exploit our instrument to estimate the model using a two-stage least squares fixed-effects estimator (2SLS-FE). The first stage can then be written as

$$AD_{rt} = \alpha + \tau \widetilde{AD}_{rt} + \zeta X_{rt} + \vartheta_r + \vartheta_t + \epsilon_{rt}. \tag{5}$$

Since we interpret $\widetilde{AD}_{rt}$ as the sales due to market power, we expect the sign of τ to

[13] To construct these markets shares we use total sales based on ex-factory prices because we do not have information on the single products and so on final prices.

be positive if manufacturers actively push their sales in areas where they have a larger market share.

It is worth reminding that the demand is not substantially driven by the patient who faces virtually no costs, and antidepressants are exclusively prescribed by physicians. Moreover, prices are set at the federal level, so manufacturers can only compete on quantity by physician detailing. As such, our instrument captures the potential influence that a manufacturer can exert in a certain area with respect to its competitors in that area. τ captures how much this market power actually influences antidepressant sales.

The estimate obtained from the first stage is then used in the second stage as

$$y_{rt} = \alpha + \beta \widehat{AD}_{rt} + \gamma X_{rt} + \vartheta_r + \vartheta_t + \epsilon_{rt}, \tag{6}$$

where $\widehat{AD}_{rt}$ is the predicted antidepressant consumption obtained from (5). β can then be interpreted as the effect of a change in the exogenous share of antidepressant consumption on mental health outcomes and, therefore, as the causal effect of antidepressant consumption on mental health outcomes. One should bear in mind that we do not estimate the average treatment effect, but instead the local average treatment effect (LATE) (Angrist et al., 1996). In particular, we measure the effect of antidepressant consumption on mental health outcomes for those who consumed antidepressants because of the manufacturer market power but would not have used antidepressant had market power been absent.

Given the count nature of our original outcomes (before the log transformation), we evaluate the robustness of our results to the use of non-linear estimation methods bases on a Poisson count data model. Following Terza et al. (2008), we take the endogeneity of antidepressant sales into account in a non-linear model using the so-called "two-stage

residual inclusion", which is a two-step procedure similar to the control function approach where the residuals from the first stage are included in the main regression equation.

5. Results

Table 2 shows the baseline results for our analysis. For each mental health outcome (hospital admissions for mental disorders, hospital admissions for depression, and suicides), we present the results of two model specifications. Model (1) includes demographic controls and year and region fixed effects. This model is our preferred specification because it includes only regional demographic characteristics, which should not be affected by changes in AD consumption. Model (2) includes physician density and unemployment rate as additional regressors, which might be affected by changes in antidepressant consumption (potentially biasing our estimates). Reported standard errors are robust and clustered at the small area level, and all reported statistics are also corrected for small sample size.

As the benchmark, we report the results obtained from OLS estimations on the within transformation (fixed effects) in the first row of Table 2. The OLS estimates indicate that a one DDD increase in antidepressant sales in a region is associated with 1.3% more hospital admissions for depression, while there is no evidence of a significant correlation with hospitalizations for mental disorders in general. The estimates of antidepressant sales on suicides are also statistically insignificant.

The second row of Table 2 reports the results of our 2SLS estimates, while we provide the respective first stage and reduced form results in the third and fourth rows. Even when we exploit the arguably exogenous variation in antidepressant sales due to differences in market shares of pharmaceutical companies', we find that an increase in antidepressant sales substantially increases hospital admissions for mental disorder and depression. The

estimated effects are also larger in magnitude than those estimated with OLS. In particular, we find that a one unit increase in DDD of antidepressant sales per 1'000 inhabitants leads to a change of hospital admission for mental health disorders of 2.2%. This effect that is mainly driven by the increase in hospitalization for depression (+ 7%).[14] As for the estimated effect of antidepressant sales on suicides, we find no evidence for a positive relationship and the point estimates suggest a slightly negative impact (less than half percentage point).

We report the first-stage results in the third row of Table 2. The estimates show that our instrument predicts antidepressant sales well. Although the value of the Kleijbergen-Paap F-statistic for weak instruments is only slightly above ten for model specification (2), it is worth noting that we have saturated the model with a full set of control variables and fixed effects, and reported the most restrictive standard errors accounting for small-sample statistics. Therefore, the results represent conservative estimates of the relationship between antidepressant sales and mental health outcomes. Reassuringly, the fourth row of Table 2 also provides evidence for the presence of significant reduced form effects, especially for hospital admissions related to depression.

Table A.4 presents estimation results for exploiting heterogeneity by gender and age groups. Our findings do not show evidence of considerable heterogeneity, except for a somewhat lower effect (4.0% vs. an average of 7.5%) on hospital admissions for depression for the elderly (43.0% in the age 65+ vs. 7.7% in the age 20-65). It is worth noting that while our outcomes vary by gender and age, antidepressant sales and the instrument do not.

[14] The estimates of the impact on all mental disorders excluding depression are smaller and not statistically significant.

5.1 Robustness checks

We use 2002 as the base year in our baseline regression model and estimate the treatment effect for the period from 2003 to 2014. As a robustness check, we keep the base year at 2002 and, in steps of one year, we use incrementally fewer data to estimate the treatment effects. In practice, we increase the time gap between the base year used to construct the share and our observation window. By doing so, we effectively decrease the sample size and, therefore, the variation that we can exploit. Nonetheless, we find for all three outcomes consistent point estimates and standard errors (Figure 4). Subfigure (a) shows an increase in the treatment effect for mental health disorders using more recent data. Moreover, the estimates for depression appear to become more precise with a decreasing sample size as indicated in Subfigure (b) of Figure 4. These findings reassure us that our instrument does indeed address the endogeneity concerns.

We report 2SLS estimates of the effect of an increase in antidepressant sales on a set of placebo outcomes in Table A.5. Specifically, we choose five causes of hospitalization that should not be affected by an increase in antidepressant sales. These causes are neoplasm (cancer), infectious diseases, bone fractures, pregnancy and diseases of the lens. They are selected to match the mean and standard deviation of our primary outcomes. Except for cancer, none of the outcomes shows any significant correlation with the instrumented antidepressant sales. In the case of cancer, however, the correlation is negative, which suggests a bias in the opposite direction. In the case of instrument endogeneity, we could expect a positive relationship between antidepressant use and hospital admissions for cancer because patients with cancer also receive antidepressant to deal with pain and related depression. More likely, the negative correlation is driven by the fact that the shares of our shift-share instrument are constructed using non-antidepressant drug

sales, and cancer drugs represent a significant component of these sales (because they are particularly expensive). Ideally, one would construct the baseline shares of our instrument by removing cancer drugs from the baseline market shares but, unfortunately, we do not have access to such disaggregated data for cancer at the product level. Reassuringly, as we increase the time gap between the base year used to construct the share, the correlation between our instrument and hospital admissions for cancer fade away (see Figure A.2).

Table A.6 shows that the 2SLS results are qualitatively similar when we take into account the count nature of the outcome variables. We apply an IV strategy to Poisson models using the control function approach. The point estimates with this method are even larger than those reported using the log-linear regression model.[15]

6. Conclusion

This research sheds light on the mental health effects of the dramatic increase in antidepressant consumption observed in Switzerland in the last two decades – a phenomenon that is also present in many other developed countries. Our contribution to this debate consists of quantifying the relationship between antidepressant sales and mental health outcomes employing an instrumental variable strategy. Using plausibly exogenous variation in local market shares of pharmaceutical companies and product innovation, we find that antidepressant sales increase hospital admissions for mental disorder by 2.2% and by 7.2% for depression, respectively. Conversely, our estimation results show no evidence for a significant effect on suicides. The results for mental health disorders are mainly driven by depression and should be interpreted with caution. In particular, as it is often the case in IV settings, our estimates allow recovering only the effect for the subpopulation of com-

[15] The difference arises mainly because of different weighting approaches in the two statistical models. Indeed, we cannot use population weights in the Poisson model and this affects the size of the first stage coefficient (0.295 versus 0.451).

pliers (LATE), which may not coincide with the average effect for the whole population (ATE).

The fact that we do not find any significant effect of antidepressant sales on suicides is worth discussing, particularly because Ludwig et al. (2009) find that the increase in SSRI use decreases suicide mortality by 5%. These authors compare SSRI use across countries and over time in the 80s and the 90s. At that time, SSRI were promoted as being more efficient than TCA, particularly in terms of reduced side effects. Because the analysis includes the introduction period of SSRI, the study probably captures the initial impact of their uptake. The current market, however, is dominated by drugs in the SSRI class.

Or results should be considered in light of the current levels of treatment with antidepressants. Evidence suggests that the prescription threshold for antidepressants has shifted towards the lower end of the severity distribution of depression, despite prescription guidelines dictate psychotherapy for mild depression and, at most, a combination of psychotherapy and pharmacotherapy for moderate cases. Our estimation results also indicate that people are hospitalized for depression in areas with higher antidepressant sales. These results could imply that the marginal patient treated with antidepressants nowadays may no longer benefit from antidepressant treatment, although our estimates indicate the LATE rather than the population-averaged effect. In particular, we measure the impact for those who are induced to consume antidepressants as a result of market power exerted by pharmaceutical companies, and would not have consumed antidepressants otherwise. A policy recommendation would be, therefore, to put measures in place to ensure adherence to the prescription guidelines and emphasize the importance of alternatives to pharmacotherapy.

Our research does not shed light on the cause of over-treatment with pharmacotherapy. Over-treatment could, for example, be the result of undercapacity of psychotherapists.

Psychotherapy is more a time-consuming form of treatment than prescribing antidepressants. Decreasing stigma and increased awareness may have led the number of patients to grow to such an extent that physicians have resorted to pharmacotherapy, even if this therapy is not the best treatment option.

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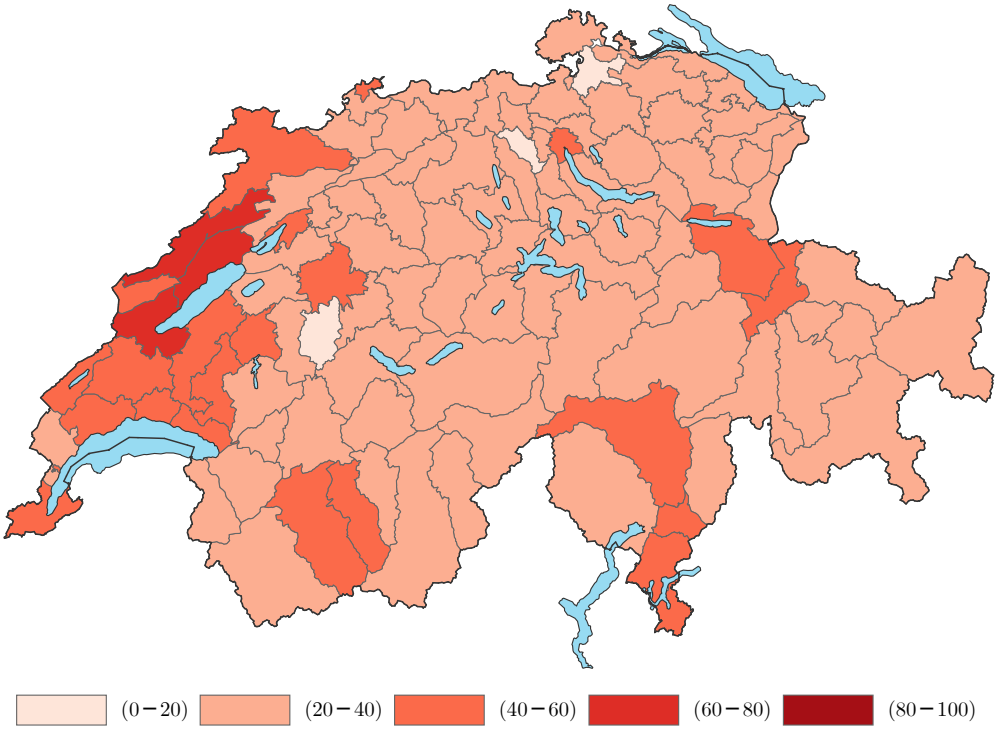
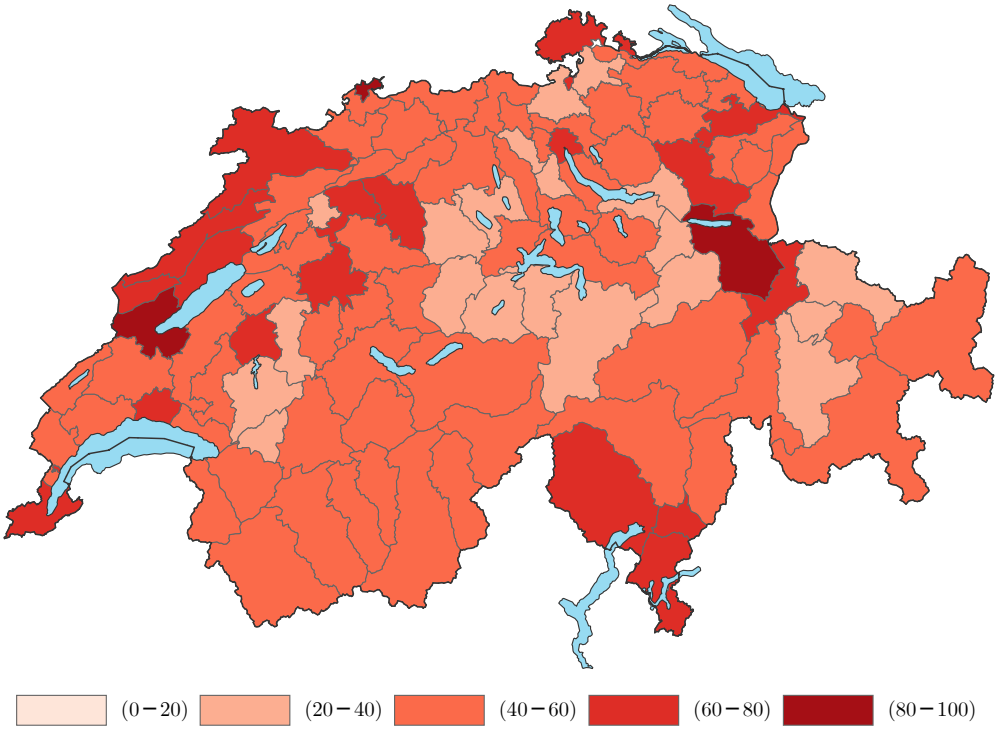


(a) Antidepressant sales in 2003



(b) Antidepressant sales in 2014

Figure 1: Antidepressant sales in Switzerland by small areas in 2003 and 2014

Notes – The figure examines antidepressant sales in Switzerland at the small area level for 2003 and 2014. To compare drug sales across regions, we classify the annual consumption according to five classes ranging from low to high where darker shades stand for higher consumption levels.

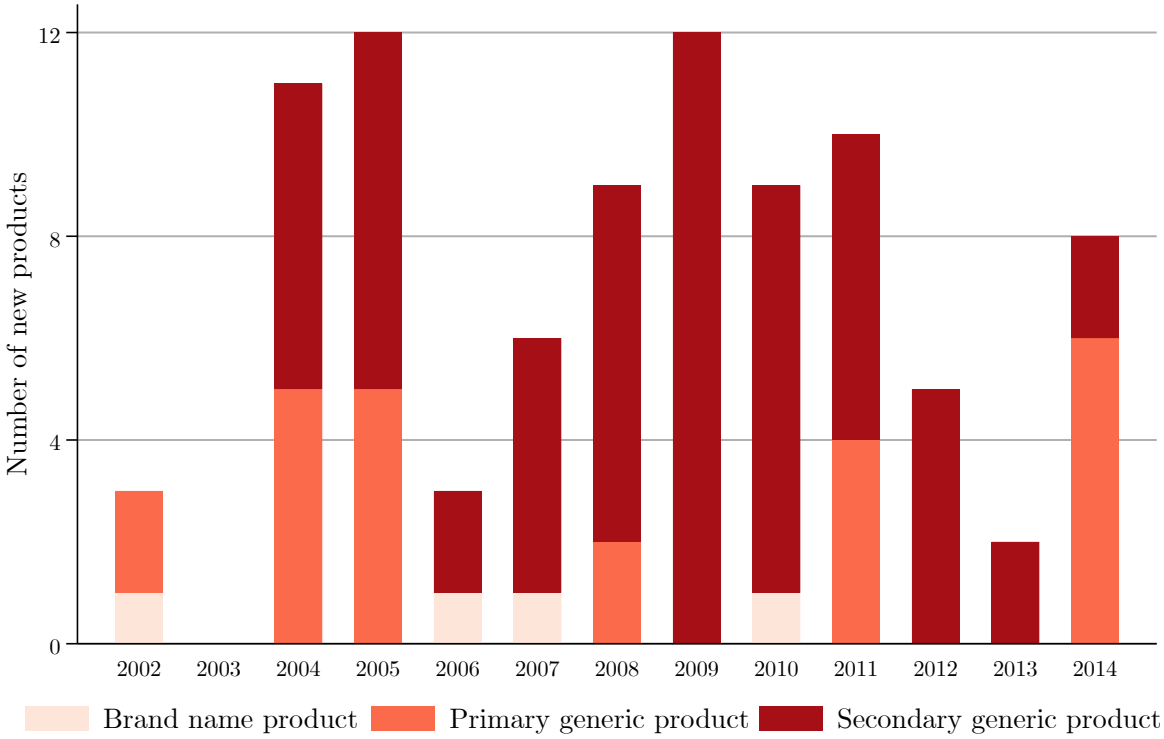
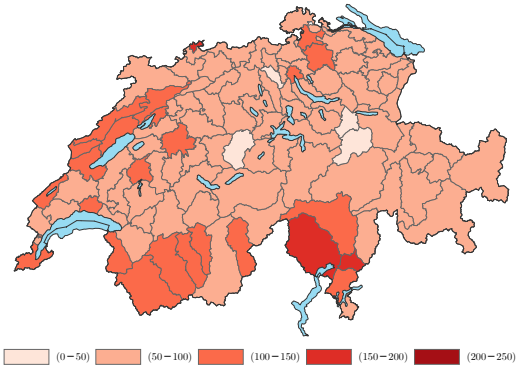
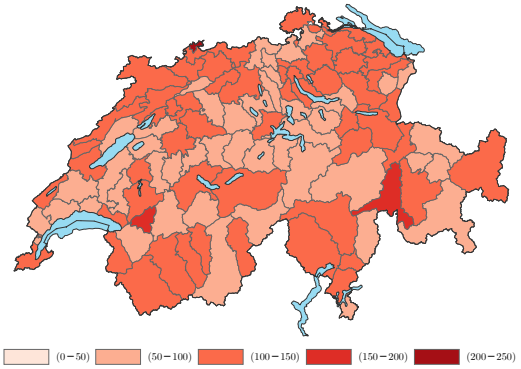


Figure 2: Introduction of new anti-depression drugs in Switzerland from 2002 to 2014

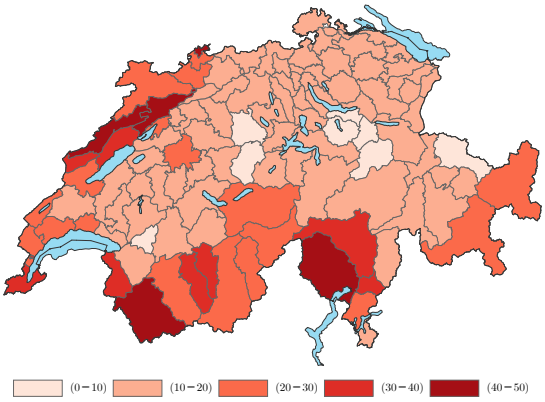
Notes – The figure shows the introduction of new antidepression drugs in Switzerland from 2002 to 2014. Light red bars indicate brand name products, red bars primary generic products, and dark red bars secondary generic products, respectively.



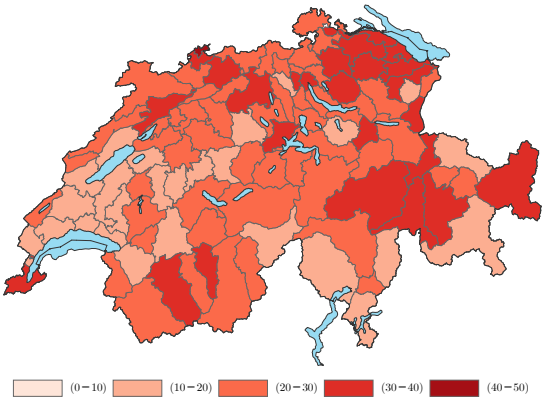
(a) Mental disorder in 2003



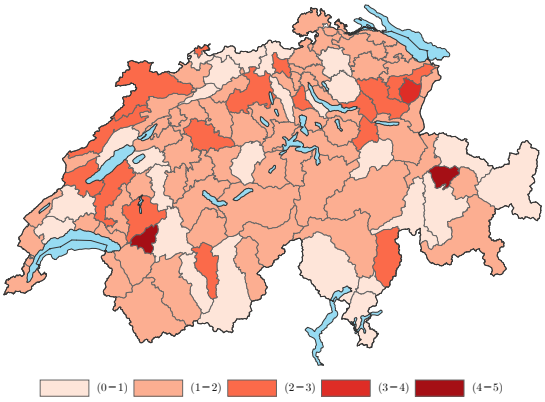
(b) Mental disorder in 2014



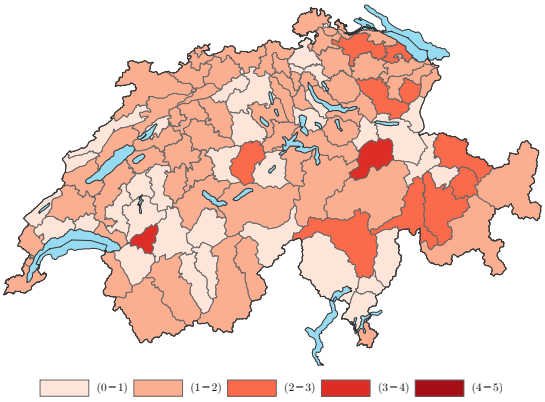
(c) Depression in 2003



(d) Depression in 2014



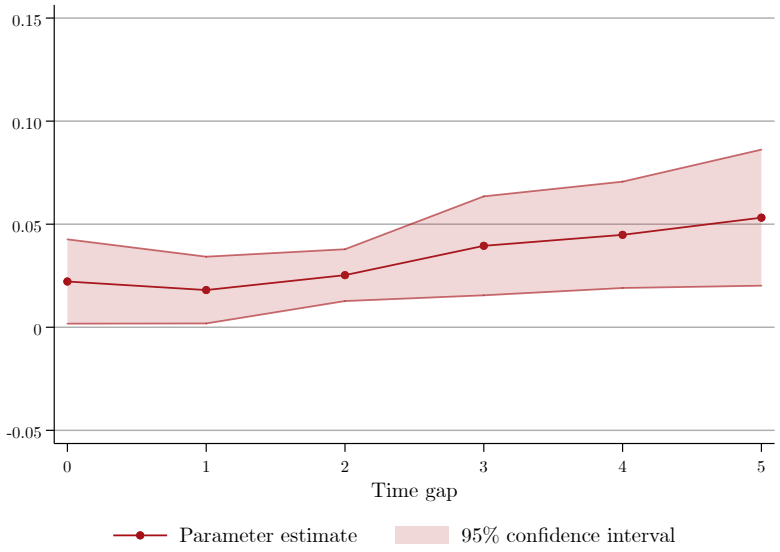
(e) Suicide in 2003



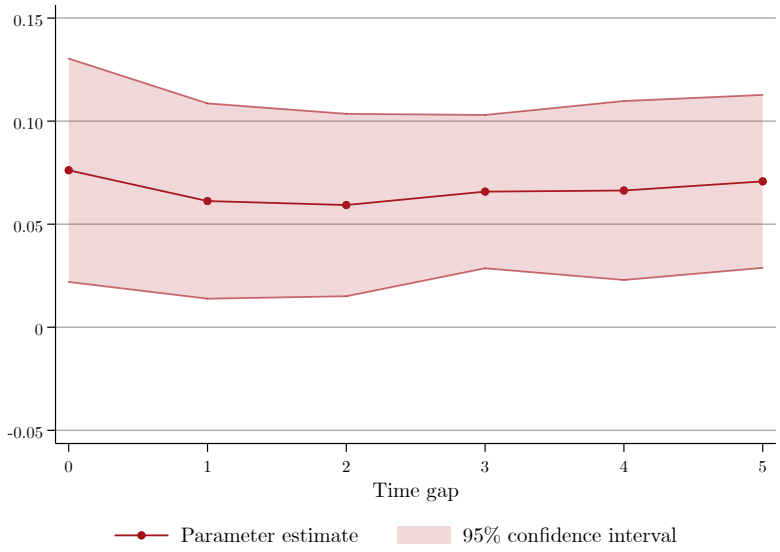
(f) Suicide in 2014

Figure 3: Mental health outcomes in Switzerland by small areas in 2003 and 2014

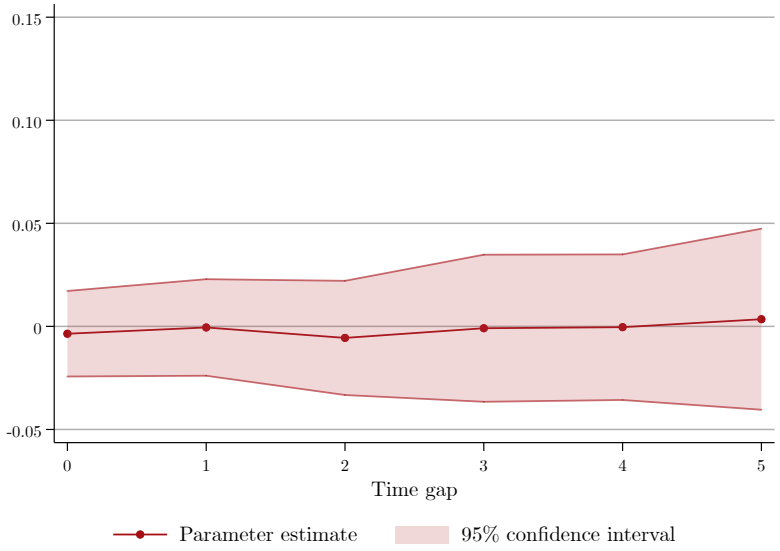
Notes – The figure classifies the prevalence of mental health disorder, depression, and suicide for 2003 and 2014. The health outcomes are categorized according to five classes ranging from low to high where darker shades stand for higher incidences.



(a) Mental disorder



(b) Depression



(c) Suicide

Figure 4: Parameter estimates by health outcome relative to 2002

Notes – The figure shows IV estimates for mental disorder (a), depression (b), and suicide (c) increasing the time gaps used for the estimation relative to the base year 2002. We report the parameter estimates and the corresponding 95% confidence intervals.

Table 1: Descriptive statistics

		Standard deviation					
	Mean	Overall	Between	Within	Δ(2003/14)	Min	Max
Antidepressant use	42.57	13.13	11.07	7.14	17.61	15.16	96.13
Mental disorder	94.23	26.43	22.73	13.65	16.54	22.16	219.08
Depression	20.54	7.32	5.02	5.35	6.12	2.89	56.07
Suicide	1.40	0.71	0.30	0.65	-0.19	0.00	6.68
Unemployment rate	2.63	1.16	1.07	0.47	-0.23	0.51	6.86
Below age 15 share	15.84	1.83	1.56	0.97	-2.32	10.03	21.29
Between age 15-65 share	67.22	1.77	1.68	0.56	-0.11	60.34	71.58
Over age 65 share	16.93	2.43	2.26	0.90	2.43	10.52	24.56
Female share	50.48	0.85	0.81	0.26	-0.50	47.92	52.94
Foreigner share	18.56	7.16	7.03	1.49	3.69	3.65	40.95
German-speaking share	64.30	37.25	37.42	0.01	-0.00	1.58	96.77
Specialists	2.30	2.34	2.28	0.59	1.08	0.00	14.98
General practitioners	6.65	1.52	1.38	0.66	0.22	2.63	11.99

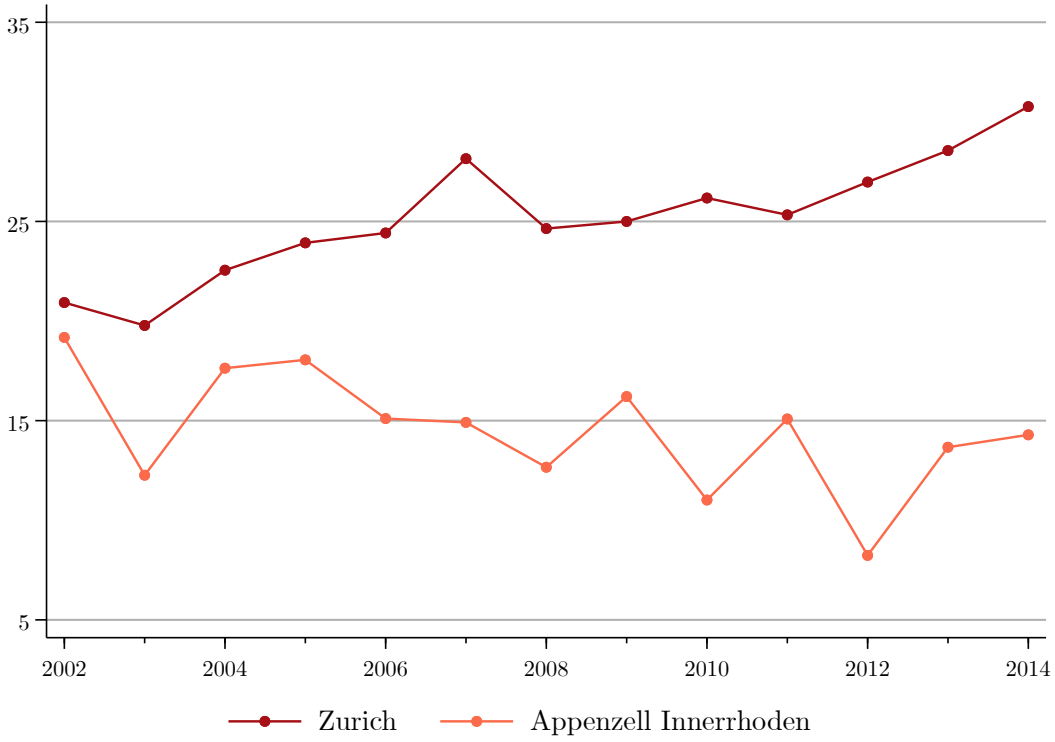
Notes – The table reports the descriptive statistics for the main variables. The statistics are obtained using annual data at the small area level for the period from 2003 to 2014. Antidepressant use is measured in terms of defined daily doses per 1,000 inhabitants and day, Mental disorder and depression are expressed in terms of hospital admissions. Specialists and general practitioners are measured by the density per 10,000 population.

Table 2: Estimates of the effect of antidepressant sales on mental health outcomes

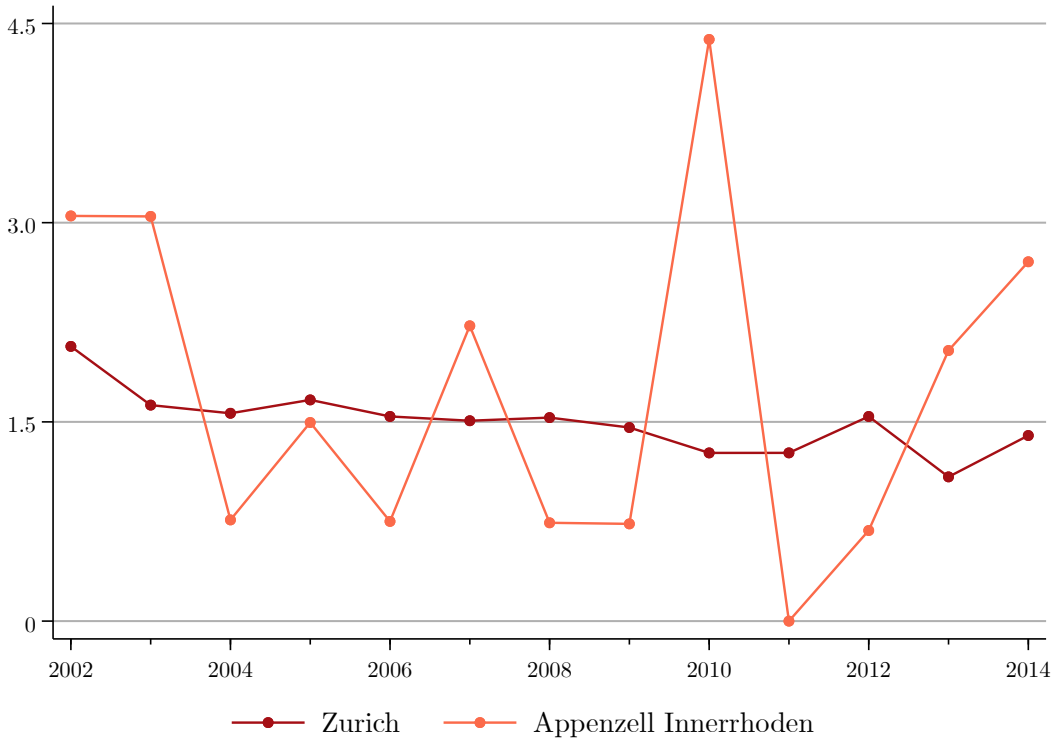
Outcomes (ln):	Mental disorder		Depression		Suicide	
Model	(1)	(2)	(1)	(2)	(1)	(2)
OLS	0.004	0.004	0.013***	0.013**	0.001	0.000
	(0.003)	(0.003)	(0.005)	(0.005)	(0.003)	(0.003)
2SLS	0.022**	0.022**	0.076***	0.072***	-0.004	-0.005
	(0.010)	(0.010)	(0.027)	(0.025)	(0.010)	(0.011)
1st stage	0.451***	0.427***	0.451***	0.427***	0.451***	0.427***
	(0.130)	(0.135)	(0.130)	(0.135)	(0.130)	(0.135)
Reduced form	0.010**	0.009**	0.034***	0.031***	-0.002	-0.002
	(0.004)	(0.004)	(0.006)	(0.005)	(0.005)	(0.005)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Physician density	No	Yes	No	Yes	No	Yes
Unemployment rate	No	Yes	No	Yes	No	Yes
Observations	1,272	1,272	1,272	1,272	1,272	1,272
Kleijbergen-Paap F	11.99	10.03	11.99	10.03	11.99	10.03

Notes – The table reports the parameter estimates for each health outcome (mental disorder, depression, and suicide) for the linear regression model and the instrumental variable regression model. We control for year and region fixed effects and population characteristics in the specification (1) and include additional control variables in the specification (2). We use cluster-robust standard errors at the small area level and report small sample statistics. Significance levels at 10%, 5%, and 1% indicated by *, **, and ***, respectively.

Supplementary materials



(a) Depression



(b) Suicide

Figure A.1: Variability of mental health outcomes for Zurich and Appenzell Innerrhoden

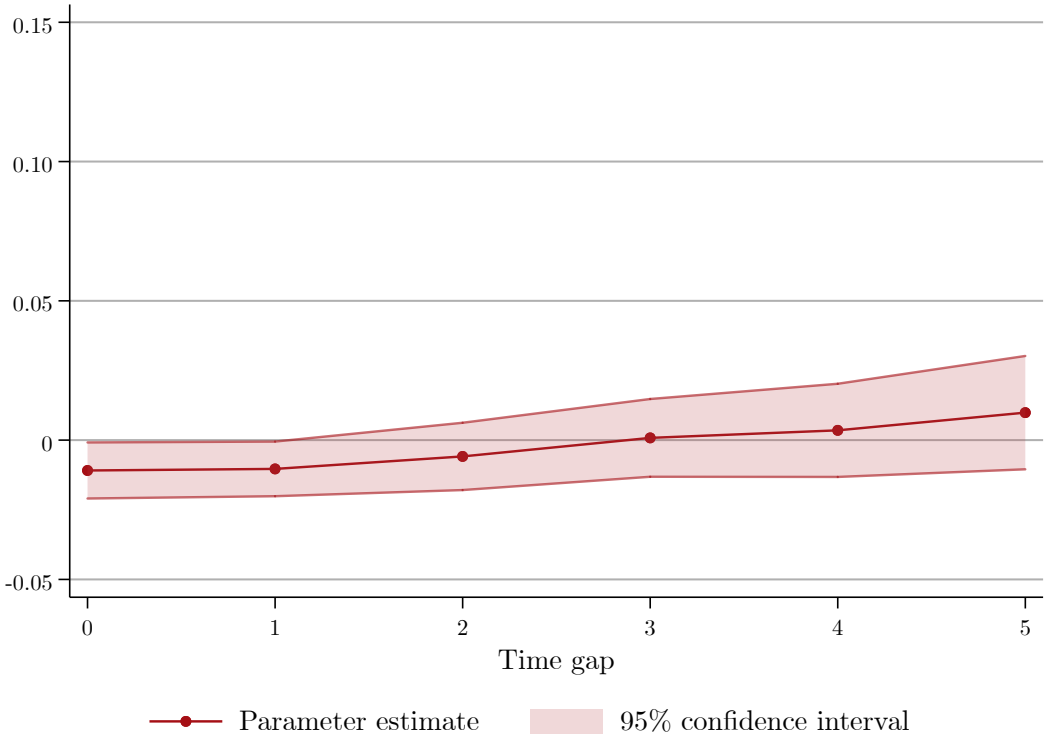


Figure A.2: Parameter estimates for placebo outcome relative to 2002

Notes – The figure shows IV estimates for cancer relative to the base year 2002. We report the parameter estimates and the corresponding 95% confidence intervals.

Table A.1: Antidepressant molecules

ATC class	Molecules
N06A4	Citalopram, Escitalopram, Fluoxetine, Fluvoxamine, Paroxetine, Sertraline
N06A5	Duloxetine, Venlafaxine
N06A9	Agomelatine, Amitriptyline, Bupropion, Clomipramine, Dibenzepin, Dosulepin, Doxepin, Imipramine, Lofepramine, Maprotiline, Mianserin, Mirtazapine, Moclobemide, Nefazodone, Nortriptyline, Opipramol, Reboxetine, Trazodone, Trimipramine

Notes – The table reports the antidepressant molecules included in the analysis. The ATC classes N06A4 (Selective serotonin re-uptake inhibitors - SSRI) and N06A5 (Serotonin norepinephrine re-uptake inhibitors - SNRI) represent recent drug classes and N06A9 (tricyclic antidepressants and others) older drug classes. We excluded the class N06A2 (herbal antidepressants) because defined daily doses cannot be calculated for herbal medicine.

Table A.2: Introduction of brand name antidepressants

Pharmaceutical company	Active ingredient	Year
Lundbeck	Escitalopram	2002
Eli Lilly	Duloxetine	2006
GSK Pharma	Bupropion	2007
Servier	Agomelatine	2010

Notes – The table reports the introduction of new brand name antidepressants by manufacturer and year. We do not include the introduction of a new mode of drug administration or package size.

Table A.3: Introduction of generic antidepressants

Pharmaceutical company	Active ingredient	Year
Sandoz	*Citalopram*	*2002*
Sandoz	*Moclobemide*	*2002*
Mepha-Teva	*Mianserin*	*2004*
Mepha-Teva	*Paroxetine*	*2004*
Sandoz	*Fluvoxamine*	*2004*
Sandoz	*Trimipramine*	*2004*
Spirig Healthcare	*Paroxetine*	*2004*
Acino Pharma	Fluoxetine	2004
Helvepharm	Citalopram	2004
Mepha-Teva	Citalopram	2004
Sandoz	Citalopram	2004
Spirig Healthcare	Citalopram	2004
Streuli Pharma	Citalopram	2004
Helvepharm	*Sertraline*	*2005*
Mepha-Teva	*Sertraline*	*2005*
Sandoz	*Sertraline*	*2005*
Spirig Healthcare	*Sertraline*	*2005*
Streuli Pharma	*Sertraline*	*2005*
Helvepharm	Paroxetine	2005
Mepha-Teva	Paroxetine	2005
Sandoz	Fluoxetine	2005
Sandoz	Paroxetine	2005
Streuli Pharma	Fluoxetine	2005
Streuli Pharma	Paroxetine	2005
Winthrop	Citalopram	2005
Mepha-Teva	Fluoxetine	2006
Sandoz	Sertraline	2006
Acino Pharma	Fluoxetine	2007
Actavis	Sertraline	2007
Helvepharm	Fluoxetine	2007
Mepha-Teva	Fluoxetine	2007
Sandoz	Sertraline	2007
Mepha-Teva	*Venlafaxine*	*2008*
Sandoz	*Venlafaxine*	*2008*
Actavis	Citalopram	2008
Adico Pharma	Fluoxetine	2008
Mepha-Teva	Citalopram	2008

continues on next page

Table A.3 – Continued from previous page

Pharmaceutical company	Active ingredient	Year
Mepha-Teva	Fluoxetine	2008
Mepha-Teva	Sertraline	2008
Semo Trading	Citalopram	2008
Semo Trading	Sertraline	2008
1a Pharma	Citalopram	2009
1a Pharma	Paroxetine	2009
1a Pharma	Sertraline	2009
Actavis	Fluoxetine	2009
Actavis	Paroxetine	2009
Actavis	Sertraline	2009
Actavis	Venlafaxine	2009
Axapharm	Fluoxetine	2009
Drossapharm	Venlafaxine	2009
Helvepharm	Venlafaxine	2009
Mepha-Teva	Sertraline	2009
Sandoz	Venlafaxine	2009
Actavis	Sertraline	2010
Helvepharm	Venlafaxine	2010
Mepha-Teva	Venlafaxine	2010
Pfizer	Sertraline	2010
Sandoz	Trimipramine	2010
Sandoz	Venlafaxine	2010
Spirig Healthcare	Fluoxetine	2010
Spirig Healthcare	Venlafaxine	2010
Helvepharm	*Mirtazapine*	*2011*
Mepha-Teva	*Mirtazapine*	*2011*
Sandoz	*Mirtazapine*	*2011*
Streuli Pharma	*Mirtazapine*	*2011*
Helvepharm	Citalopram	2011
Pfizer	Citalopram	2011
Pfizer	Sertraline	2011
Pfizer	Venlafaxine	2011
Sandoz	Trimipramine	2011
Sanofi-Aventis	Trimipramine	2011
Actavis	Mirtazapine	2012
Mepha-Teva	Venlafaxine	2012
Pfizer	Citalopram	2012

continues on next page

Table A.3 – Continued from previous page

Pharmaceutical company	Active ingredient	Year
Sandoz	Mirtazapine	2012
Spirig Healthcare	Mirtazapine	2012
Actavis	Citalopram	2013
Actavis	Fluoxetine	2013
Actavis	*Escitalopram*	*2014*
Axapharm	*Escitalopram*	*2014*
Helvepharm	*Escitalopram*	*2014*
Mepha-Teva	*Escitalopram*	*2014*
Sandoz	*Escitalopram*	*2014*
Spirig Healthcare	*Escitalopram*	*2014*
Actavis	Citalopram	2014
Actavis	Venlafaxine	2014

Notes – The table reports the introduction of generic antidepressants by manufacturer and year. First introducers are highlighted in italic. We do not include the introduction of a new mode of drug administration or a different package size.

Table A.4: Estimates of the effect of antidepressant sales on mental health outcomes by sex and age groups

Outcomes (ln):	Mental disorder		Depression		Suicide	
Model	(1)	(2)	(1)	(2)	(1)	(2)
			Males			
2SLS	0.018	0.018	0.074**	0.067**	-0.012	-0.013
	(0.011)	(0.011)	(0.031)	(0.028)	(0.013)	(0.014)
			Females			
2SLS	0.026**	0.025***	0.076***	0.073***	0.020	0.022
	(0.010)	(0.009)	(0.025)	(0.023)	(0.016)	(0.017)
			Age < 20			
2SLS	0.011	0.008	0.076***	0.079***	0.004	0.002
	(0.012)	(0.010)	(0.026)	(0.027)	(0.016)	(0.018)
			Age $20 - 65$			
2SLS	0.025**	0.025**	0.082**	0.077***	0.002	0.001
	(0.012)	(0.012)	(0.032)	(0.029)	(0.011)	(0.011)
			Age > 65			
2SLS	0.019*	0.019*	0.046***	0.043***	-0.036	-0.040
	(0.010)	(0.010)	(0.016)	(0.015)	(0.022)	(0.025)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Physician density	No	Yes	No	Yes	No	Yes
Unemployment rate	No	Yes	No	Yes	No	Yes
Observations	1,272	1,272	1,272	1,272	1,272	1,272
Kleijbergen-Paap F	11.99	10.03	11.99	10.03	11.99	10.03

Notes – The table reports the second stage IV estimates for each health outcome (mental disorder, depression, and suicide) separated by gender and age. We control for year and region fixed effects and population characteristics in the specification (1) and include additional control variables in the specification (2). We use cluster-robust standard errors at the small area level and report small sample statistics. Significance levels at 10%, 5%, and 1% indicated by *, **, and ***, respectively.

Table A.5: Placebo estimates using alternative hospitalization outcomes

Outcomes (ln):	Neoplasms	Infectious diseases	Bone fractures	Pregnancy and childbirth	Diseases of the lens
2SLS	-0.011**	0.001	0.003	0.010	0.072*
	(0.005)	(0.007)	(0.009)	(0.007)	(0.043)
Year FE	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Demographics	Yes	Yes	Yes	Yes	Yes
Observations	1,272	1,272	1,272	1,272	1,272
Kleijbergen-Paap F	11.99	11.99	11.99	11.99	11.99
Mean	116.03	35.55	150.97	111.36	7.72
Within SD	16.11	9.41	23.34	11.28	8.02
Between SD	15.15	6.97	27.91	13.07	5.12

Notes – The table reports the second-stage IV estimates for the placebo outcomes. We control for year and region fixed effects and population characteristics in the regression models. The placebo outcomes (ICD10 codes) are neoplasms (C00-C97 & D00-D09 & D10-D36 & D37-D48), certain infectious and parasitic diseases (A-B), bone fractures (S), sexually transmitted diseases (A50-A64), and pregnancy, childbirth and the puerperium (O). We use cluster-robust standard errors at the small area level. Significance at 10%, 5%, and 1% indicated by *, **, and ***, respectively.

Table A.6: Poisson estimates of the effect of antidepressant sales on mental health outcomes

Outcomes:	Mental disorder		Depression		Suicide	
Model	(1)	(2)	(1)	(2)	(1)	(2)
Poisson	0.001	0.001	0.012**	0.009**	0.007	0.005
	(0.002)	(0.002)	(0.005)	(0.004)	(0.006)	(0.005)
Poisson 2SLS	0.030**	0.033**	0.119***	0.123***	0.005	-0.005
	(0.013)	(0.015)	(0.023)	(0.026)	(0.030)	(0.037)
Residuals	-0.030**	-0.033**	-0.114***	-0.119***	-0.001	0.008
	(0.013)	(0.016)	(0.024)	(0.026)	(0.029)	(0.037)
1st stage	0.295***	0.252***	0.295***	0.252***	0.295***	0.252***
	(0.077)	(0.077)	(0.077)	(0.077)	(0.077)	(0.077)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Physician density	No	Yes	No	Yes	No	Yes
Unemployment rate	No	Yes	No	Yes	No	Yes
Observations	1,272	1,272	1,272	1,272	1,272	1,272
Kleijbergen-Paap F	11.99	10.03	11.99	10.03	11.99	10.03

Notes – The table reports the parameter estimates for each mental health outcome (mental disorder, depression, and suicide) for the Poisson model and the Poisson instrumental variable regression model. We control for year and region fixed effects and population characteristics in the specification (1) and include additional control variables in the specification (2). We use cluster-robust standard errors at the small area level. Significance levels at 10%, 5%, and 1% indicated by *, **, and ***, respectively.

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