MAGKS

Joint Discussion Paper Series in Economics

by the Universities of
Aachen • Gießen • Göttingen
Kassel • Marburg • Siegen

ISSN 1867-3678

No. 05-2025

Maximilian M. Gail, Georg Götz, Daniel Herold, and Jan Schäfer

Evaluation of a Partial Ban of Rx-Rebates in Germany Using Difference-in-Differences

Evaluation of a Partial Ban of Rx-Rebates in Germany Using Difference-in-Differences

Maximilian M. Gail* Georg Götz* Daniel Herold*
Jan Schäfer*

February 4, 2025

Abstract

In December 2020, Germany implemented a policy restricting online pharmacies from offering rebates on prescription drugs to members of the statutory health insurance. This policy change created a natural experiment, allowing us to analyze its impact on the pharmaceutical market using Difference-in-Differences. Utilizing a novel dataset, we find that the ban led to a shift in consumer behavior, increasing offline pharmacy Rx sales by 1.36 % to 1.65 %. However, the policy's effects were unevenly distributed across pharmacies. While all pharmacies experienced some benefit, the impact was disproportionately larger for higher-revenue pharmacies. For instance, pharmacies in the lowest revenue decile saw a modest annual profit increase of € 1,360, whereas those in the highest decile gained more than five times that amount. Our findings indicate that the introduction of VOASG alone was insufficient to reverse the declining trend in pharmacy numbers in Germany. To strengthen the comprehensive supply of pharmaceuticals to the general population, additional reforms are necessary.

Keywords: Pharmacies, Prescription Drugs, Resale Price Maintenance, Regulation, Public Health

JEL Codes: L5, I18

*Chair for Industrial Organization, Regulation and Antitrust, Department of Economics, Justus Liebig University Giessen. Licher Strasse 62, 35394 Giessen. Corresponding author: daniel.herold@wirtschaft.uni-giessen.de.

1 Background

The optimal allocation of healthcare resources, including pharmaceuticals, is a critical public health concern in many countries (Mays et al., 2009; Herwartz and Schley, 2018; Haschka et al., 2020; Li and Liu, 2021). While the specific roles of pharmacies vary across countries, the OECD's characterization of pharmacists as "managing the distribution of medicines to consumers/patients and supporting their safe and efficacious use" provides a generally applicable framework (OECD, 2023). German law (specifically §1 of the Pharmacy Act (ApoG)) requires brick-and-mortar pharmacies to provide the general population with access to medications. However, the number of pharmacies has significantly decreased, dropping by roughly 12.5% from 2010 (21,441) to 2020 (18,753) (ABDA, 2024, p. 9). This decline coincides with a rise in competition from foreign online pharmacies. Their market share for over-the-counter (OTC) drugs increased from around 5% in 2008 to 20% by 2020 (ABDA, 2021; Statista, 2024). Initially, resale price maintenance (RPM) for prescription (Rx) drugs limited price competition to OTC medications. However, a 2016 European Court of Justice ruling allowed online pharmacies to also offer discounts on Rx drugs (Albrecht et al., 2020).

In the light of these developments, in December 2020 the German government implemented a law that was supposed to strengthen the comprehensive supply of pharmaceuticals to the general population by supporting brick-and-mortar pharmacies. Accordingly, the name of the law was "Vor-Ort-Apotheken Stärkungsgesetz" (Local Pharmacy Support Act), henceforth referred to as VOASG. This law partially restricts online rebates by prohibiting them for Rx drugs sold to members of the statutory health insurance scheme, but allows them for privately insured individuals (details on the German health insurance system in Section 2.2). This article investigates the impact of the VOASG on sales and rents in the Rx market using a difference-in-differences (DiD) approach. By comparing the dispensation of Rx drugs to members of the statutory health insurance (treatment group) with those to the privately insured and self-pay patients (control group), we can isolate the effect of the policy change. The VOASG only affected Rx drugs dispensed to statutory health insurance members, leaving prescriptions to the privately insured and self-pay patients unaffected. This differential impact allows us to identify the causal effect of the policy.

We employ a novel dataset for this study, constructed from high-frequency sales data provided by the major merchandise information system (MIS) suppliers in Germany. This dataset encompasses individual transaction data from approximately 9,231 offline pharmacies, representing nearly half of all German pharmacies, for the period January 1, 2018, to October 31, 2022 (see Section 2.1).

We find that the partial ban on rebates led to an increase in offline sales of around 1.36 to 1.65 % for an average brick-and-mortar pharmacy compared to a counterfactual scenario in which rebates would not have been banned. Given that the demand for Rx drugs can be considered price inelastic, any increase in offline sales should correspond to a decrease in online sales by the same amount.

Our findings reveal that a substantial portion of consumers respond to price differences and rebates for Rx drugs by selecting the more affordable retail channel. This insight is particularly relevant in light of the 2016 European Court of Justice ruling (Case No.: C-148/15) mentioned above, which legalized rebates offered by foreign online pharmacies. In this ruling, the judges claimed that the German government had failed to show that RPM was an effective tool to achieve the alleged goal of securing the comprehensive supply of pharmaceuticals to the general population. Our research provides empirical evidence that consumers are price-sensitive, suggesting that online rebates could potentially erode offline sales and profitability.

Given these findings, we further investigate whether the policy change successfully mitigated large-scale pharmacy closures. Economic theory posits that market exit occurs when opportunity costs exceed revenues, resulting in negative economic profits (Jehle and Reny, 2011, Ch. 4). Ceteris paribus, pharmacies with lower revenues are more susceptible to market exit. To evaluate the impact of VOASG, we stratified the sample into revenue deciles and calculated the DiD effect for each decile.

Our analysis reveals that the effects for the lowest seven deciles are relatively similar, while the effect in the three highest deciles is around 40% to 140% stronger. This suggests that larger pharmacies benefited disproportionately from the rebate ban compared to smaller pharmacies. These findings indicate that the law, against its stated goal, did not significantly support pharmacies at risk of market exit. We estimated the additional *annual* profits generated by the rebate ban for pharmacies in the first and tenth deciles, which were approximately €1,360 and €7,690, respectively. Notably, the *additional annual profit* for the lowest decile equates to around one third of the average *monthly* income of an employee in Germany in 2021 (Destatis, `https://t.ly/N2dJq`). The findings also indicate that the majority of pharmacies experienced only a mild increase in profits, with a median increase in profits of €3,246. Given these relatively modest gains, it seems unlikely that the policy had a substantial impact on the market. This is corroborated by the developments in 2021-2023, when another 6.3% of pharmacies closed.

This article contributes, first, to the growing body of research on public health service provision. While many studies have focused on hospitals or physicians in specific countries such as the US (Mays et al., 2009; Duminy et al., 2022), China (Li and Liu, 2021), and Germany (Herwartz and Schley, 2018; Haschka et al., 2020), our research examines the role of pharmacies. These establishments often serve as the final link in the pharmaceutical supply chain, delivering medications to the general public (Inoue et al., 2016; Raza et al., 2022). Previous research on pharmacies has primarily investigated specific services, such as their role in delivering primary care or providing non-prescription medications (Smith, 2009; Agomo, 2012; Perraudin et al., 2016; Costa et al., 2019). Our research, in contrast, analyzes how price competition affects pharmacy profitability and, consequently, the financial sustainability of their services. By examining this aspect, our study adds a new dimension to the understanding of pharmacy's role in public health.

Second, this article contributes to the literature on digitization, particularly the debate surrounding the substitutability of offline and online services (Brynjolfsson and Smith, 2000; Brown and Goolsbee, 2002; Sinai and Waldfogel, 2004; Jin and Kato, 2007; Goldmanis et al., 2010; Cavallo, 2017; Couture et al., 2021). While research on digital public health explores how digitization can improve population health (Iyamu et al., 2022; Wong et al., 2022; Yurkovich et al., 2024), our study focuses on the pharmacy sector. Specifically, we investigate the extent to which online pharmacies complement or substitute traditional brick-and-mortar pharmacies in supplying pharmaceuticals to the public (Coenen et al., 2011; an der Heiden and Meyrahn, 2017). Our findings suggest that price differentials impact consumer behavior. When price disparities exist between online and offline channels, there is a statistically and economically significant fraction of consumers that chooses the cheaper option. This price sensitivity has important implications for policymakers aiming to maintain a network of brick-and-mortar pharmacies of a certain density. As online pharmacies, especially those offering rebates, can cannibalize the market share of traditional pharmacies, policymakers should consider the potential economic consequences of price competition.

Third, we contribute to the research on RPM (Telser, 1960; Marvel and McCafferty, 1985; Hunold and Muthers, 2017). While RPM can potentially eliminate freeriding by online retailers and mitigate double marginalization, it also suppresses downstream price competition (Elzinga and Mills, 2008). In the pharmacy market, the situation is more complex. Countries often pursue health policy objectives that extend beyond market-based outcomes, such as ensuring a certain number or quality of pharmacies (Wambach et al., 2018). Our findings indicate that RPM shifts profits towards brick-and-mortar pharmacies, thereby contributing to the achievement of these objectives. However, the introduction of VOASG alone was insufficient to reverse the declining trend in pharmacy numbers in Germany. Other structural factors (in particular, pharmacies' remuneration) seem to exert a more substantial influence on the decline of offline pharmacies than RPM.

The article is structured as follows. In Section 2, we discuss the data and our identification strategy. Section 3 contains the results of our empirical analysis. In Section 4, we discuss how the identified effects differ between pharmacies with different revenues as well as limitations of the study. Section 5 concludes.

2 Methods

In this section, we outline the methodological approach employed to identify the impact of the partial ban on online Rx rebates on the market. We begin in Section 2.1 by describing the dataset we assembled for our analysis. Subsequently, in Section 2.2, we provide a non-technical overview of our identification strategy. A more technical implementation of our identification strategy is detailed in Appendix A.

2.1 Data

In our empirical analysis, we use sales data for 5,487 pharmacies. This sample is derived from a larger dataset of 9,231 pharmacies, which we adjusted for our analysis as described in Appendix A.2. The final sample represents 29.13% of the total number of 18,839 pharmacies as of September 29, 2020 (see Figure B.1 for a map of the geographical distribution).

Through the balancing procedure and the application of these data constraints, we retain approximately 68.2% of the total sales data from the unrestricted dataset. Ultimately, we assemble two distinct annual datasets, ranging from 2018 to 2021: one categorized by 2-digit zip code and another by individual pharmacy. Each dataset contains comprehensive transaction details for each pharmacy, including sales volumes, the AVP (retail price), and other product-specific information. For further details on the data processing steps, including balancing, constraints, and aggregation, refer to Appendix A.2.

2.2 Identification Strategy

In this section, we outline our identification strategy, which leverages the differential impact of the VOASG on specific population segments. This natural experiment allows us to apply a DiD approach and conduct an event study to assess causal effects (Cunningham, 2021, Chapter 9). Prescriptions to members of the statutory health insurance, directly affected by the VOASG, form the treatment group, while prescriptions to privately insured individuals and self-pay patients, unaffected by the reform, serve as the control group. By comparing the differential changes in the dispensation of Rx drugs between these groups, we isolate the causal effect of the VOASG. To provide further clarity, we first offer a brief overview of the German insurance system, with a particular focus on the prescription drug dispensation scheme.

In Germany, prescription drugs are prescribed by physicians and dispensed by both traditional and online pharmacies. To access these medications, members of the statutory health insurance are typically required to make co-payments based on AVP, contributing a portion of the drug's cost. Private insurance offers a range of reimbursement schemes, often involving initial out-of-pocket expenses and subsequent reimbursement by the insurer. (For a more detailed explanation, see Section C.2.) Thus, both systems generally adhere to standardized reimbursement rates for prescribed medications. Irrespective of the specificities of each insurance scheme, drug prices are the same in the offline and online channels irrespective of insurance. The same is true for self-pay patients. The only difference in the price dimension is that, after the introduction of VOASG, members of the statutory health insurance were no longer entitled to rebates for online purchases.

The VOASG came into effect on December 15, 2020. As described above, a central aspect of this legislation is the prohibition of foreign online pharmacies from offering rebates to individuals insured under the statutory health insurance. However, these pharmacies are still permitted to provide rebates to privately insured consumers (Federal Ministry of Health, `https://www.bundesgesundheitsministerium.de/apotheken.html`).

Rebates granted by online pharmacies usually range from €2.50 to €10 and take the form of vouchers. In relation to the fundamental differences between public and private health insurance (premium structures, reimbursement mechanisms, service quality) these rebates are of minor importance.

There are also notable barriers to switching between the two systems. Individuals usually can only switch when their employment status changes in a special way in terms of income and type of employment. The policy can thus be considered exogenous to the individuals' choice regarding insurance schemes.

The demand for prescription drugs is generally inelastic due to their nature (Gatwood et al., 2014; Yeung et al., 2018): a patient's need for medication is often diagnosed by a physician and is not easily deferred. Moreover, as the patient's insurance typically covers the majority of the cost, co-payments are of minor importance. This suggests that patients are unlikely to forego necessary medication solely due to the absence of rebates. While rebates potentially influence a patient's choice of pharmacy (online or offline), their impact on overall drug consumption is likely minimal. Given the inelastic nature of demand, any shift in offline sales is expected to be accompanied by a similar shift in online sales.

Given that pharmacy compensation is directly tied to the number of packages dispensed, we utilize this metric to assess the impact of VOASG. This approach is further justified by the fact that market data is predominantly reported in terms of sales or revenue, eliminating the need for additional conversions. A more in-depth discussion is presented in the following section.

3 Results

To gain an initial understanding of a potential DiD effect, we compared the mean sales of the treatment and control groups before and after the introduction of VOASG. Post-VOASG, prescription drug sales in the treatment group exhibited a 1.63% increase relative to the control group. A detailed summary of this finding is provided in Appendix B.1 (Figure B.2), together with further descriptive statistics.

To estimate the causal impact of VOASG, we use a two-way fixed effects (TWFE) DiD estimation. Additionally, an event study is conducted to assess the common trends assumption by examining pre-treatment periods before the implementation of VOASG (Cunningham, 2021, Chapter 9.4). Technical details on the estimation procedures can be found in Appendix B.

As covariates, we include (i) the weighted quantity of doses of Rx drugs dispensed and (ii) the fraction of customers that are members of the statutory health insurance.

Covariate (i) is calculated based on Germany's N-classification system. This system categorizes pharmaceutical packages into three sizes: N1 (10 doses), N2 (30 doses), and N3 (100 doses). While not exact, this system provides a reasonable approximation of package sizes. To account for potential variations in package sizes that could influence our results, we calculate a weighted average of package sizes at the 2-digit zip code or pharmacy level for each group. For instance, a combination of 15 N1 and 5 N2 packages would equate to approximately 300 doses, which corresponds to a weighted average of 20 doses. By controlling for this covariate, we mitigate the impact of package size differences on our analysis (see Appendix A.2 for more details).

Covariate (ii) accounts for the relative share of individuals enrolled in statutory and private health insurance. This covariate is necessary to mitigate the potential confounding effects of significant shifts in insurance enrollment. Due to data constraints, this covariate is measured at the national level and varies annually, essentially functioning as a time trend.

Table 1 presents the results of the TWFE DiD model (see Equation (B.1) in Appendix B). We estimate two model specifications: a baseline model (A) and a model with a time-trend (B). For each specification, Column (1) presents results aggregated at the 2-digit zip code level with robust standard errors. Columns (2) to (4) reports the results for an aggregation at pharmacy-level. Column (2) uses robust standard errors, while Columns (3) and (4) cluster standard errors at the 2-digit zip code level, or at the 2-digit zip code and insurance group level, respectively.

Table 1 shows a DiD effect that ranges from 0.0136 to 0.0165. All results are statistically significant at the 1 % level. These effects represent the average treatment effect on the treated (ATT) and can be interpreted as percentage changes. Therefore, due to the introduction of the VOASG, sales increased by approximately 1.36 % to 1.65 % compared to a counterfactual scenario without the policy. Further discussion of the result follows in Section 4.

The remainder of this section presents the results of an event study approach. The technical details are presented in Appendix B.

	(1)	(2)	(3)	(4)
Specification A: Sales in Packages				
DiD-Coefficient	0.0155***	0.0165***	0.0165***	0.0165***
	(0.0039)	(0.0023)	(0.0015)	(0.0032)
Fraction of Members in Insurance	1.5718	1.1123	1.1123	1.1123
	(1.8638)	(1.2091)	(1.1569)	(1.7127)
Weighted Average of Doses	0.0013	-0.0006	-0.0006	-0.0006
	(0.0030)	(0.0006)	(0.0009)	(0.0008)
Observations	760	43,896	43,896	43,896
Adj. R2	0.9997	0.9938	0.9938	0.9938
FE: Year	X	X	X	X
FE: 2 digit zip code & Treated	X			
FE: Pharmacy & Treated		X	X	X
Std. Errors	Robust	Robust	by: 2-digit-zip code	by: 2-digit-zip code & Treated
Specification B: Sales in Packages with Trends				
DiD-Coefficient	0.0136***	0.0149***	0.0149***	0.0149***
	(0.0048)	(0.0029)	(0.0018)	(0.0036)
Weighted Average of Doses	0.0012	-0.0006	-0.0006	-0.0006
	(0.0030)	(0.0006)	(0.0009)	(0.0008)
Time Trend of Treatment-Group	0.0017	0.0013	0.0013	0.0013
	(0.0017)	(0.0011)	(0.0010)	(0.0015)
Observations	760	43,896	43,896	43,896
Adj. R2	0.9997	0.9938	0.9938	0.9938
FE: Year	X	X	X	X
FE: 2 digit zip code & Treated	X			
FE: Pharmacy & Treated		X	X	X
Std. Errors	Robust	Robust	by: 2-digit-zip code	by: 2-digit-zip code & Treated

Note:
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1: Results of the DiD-estimation.

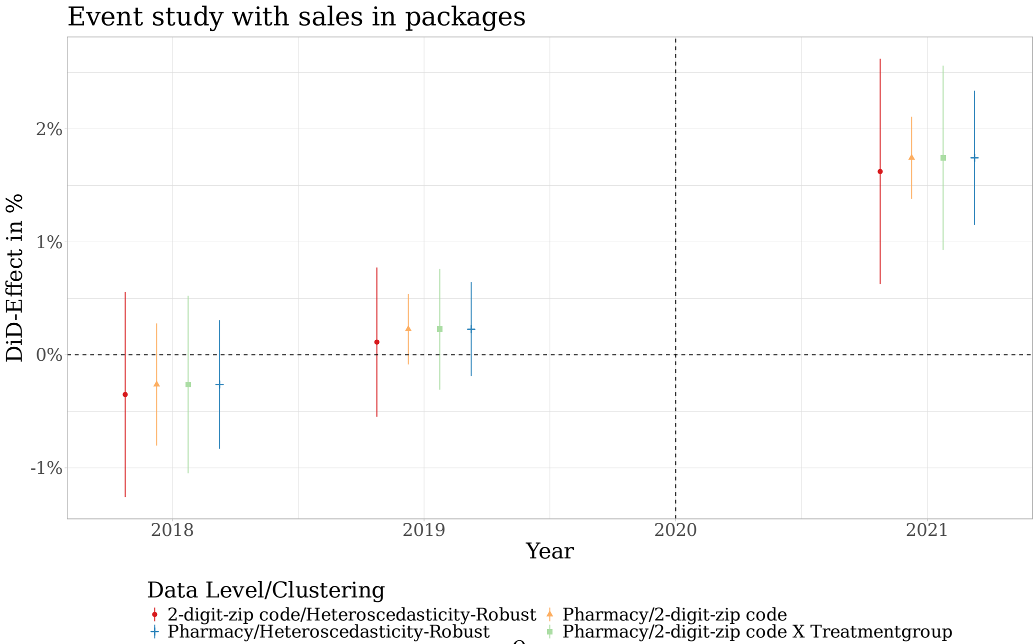

Figure 1: Event study results with 99 % confidence intervals.

The event study provided in Figure 1 highlights that all pre-treatment coefficients are statistically insignificant and close to zero. The ATT for 2021 is estimated at 0.0162 and 0.0174, maintaining statistical significance similar to the DiD estimation. Thus, results from the event study align closely with those of the regression analyses above (see Figure B.2).

As explained in Section 2.2, we measure drug dispensation in terms of packages. To account for variations in package sizes, we employ a covariate based on the N-classification system, as described above. As a robustness check, we conduct additional analyses using approximated dosages derived from the N-classification system. Further details and results are provided in Appendix A.2.

4 Discussion

In this section, we discuss our findings in the context of the policy objective, which aimed to support (small) brick-and-mortar pharmacies. The section is divided into two parts. In Section 4.1, we extend our analysis to examine how pharmacies with different revenue levels benefited from the partial ban on rebates. In Section 4.2, we address the limitations inherent to our study.

4.1 Distributional Effects

As explained in Section 1, the VOASG was introduced to strengthen the comprehensive supply of pharmaceuticals to the general population during a period of a drastically shrinking number of brick-and-mortar pharmacies. To evaluate the effect of the policy change on the number of pharmacies in the market, we extend the analysis presented in Section 3.

As explained in the introduction, all else equal, pharmacies with lower revenues are more exposed to market exit. We therefore categorize pharmacies into deciles based on their revenue. The first decile includes the 10% of pharmacies with the lowest revenue, the second decile includes the next 10% with the second-lowest revenue, and so on. We then interact the DiD effect estimated in Section 3 with a dummy variable indicating each decile. A time trend is included to control for potentially diverging evolutions between the two insurance groups. The results of this analysis are presented in Table 2. Technical details are outlined in the Appendix (Section C.3, Equation (C.1)).

	(1)	(2)	(3)
Weighted Average of Doses	-0.0017***	-0.0017**	-0.0017**
	(0.0005)	(0.0007)	(0.0007)
Time Trend of Treatment-Group	0.0016*	0.0016	0.0016
	(0.0009)	(0.0010)	(0.0013)
DiD for Decile 1	0.0128***	0.0128**	0.0128**
	(0.0047)	(0.0053)	(0.0056)
DiD for Decile 2	0.0111***	0.0111***	0.0111**
	(0.0043)	(0.0038)	(0.0046)
DiD for Decile 3	0.0107***	0.0107**	0.0107**
	(0.0040)	(0.0041)	(0.0043)
DiD for Decile 4	0.0146***	0.0146***	0.0146***
	(0.0042)	(0.0041)	(0.0044)
DiD for Decile 5	0.0127***	0.0127***	0.0127***
	(0.0040)	(0.0034)	(0.0044)
DiD for Decile 6	0.0092**	0.0092**	0.0092**
	(0.0037)	(0.0036)	(0.0040)
DiD for Decile 7	0.0131***	0.0131***	0.0131***
	(0.0037)	(0.0030)	(0.0036)
DiD for Decile 8	0.0182***	0.0182***	0.0182***
	(0.0038)	(0.0030)	(0.0039)
DiD for Decile 9	0.0208***	0.0208***	0.0208***
	(0.0037)	(0.0031)	(0.0037)
DiD for Decile 10	0.0190***	0.0190***	0.0190***
	(0.0040)	(0.0039)	(0.0047)
Observations	43,896	43,896	43,896
Adj. R2	0.9959	0.9959	0.9959
FE: Year	X	X	X
FE: Pharmacy & Treated	X	X	X
FE: Deciles	X	X	X
Std. Errors	Robust	by: 2-digit-zip code	by: 2-digit-zip code & Treated

Note:
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Results of the DiD-estimation for revenue deciles.

The panels presented in Table 2 are defined in Section 3. The coefficients for "DiD for Decile x" capture the interaction between the DiD effect and the respective decile. These coefficients should be interpreted in the same manner as the DiD coefficient in Table 1, but are specific to each decile. For instance, a coefficient value of 0.0128 for "DiD for Decile 1" indicates that, on average, sales of brick-and-mortar pharmacies in the lowest revenue decile (treatment group) increased by 1.28 %, holding all else constant.

The results reveal a notable asymmetry in the magnitude of the effects across different revenue deciles. Specifically, the increase in Rx sales for deciles one to seven ranges from approximately 0.92 % to 1.46 % across all panels in Table 2. In contrast, the effect for the highest three deciles is 40 % to 140 % larger, ranging from 1.82 % to 2.16 %. In other words, pharmacies with higher revenues seem to have benefited more from the partial ban on rebates than those with lower revenues. This disparity is further accentuated by the fact that the results in Table 2 are expressed in relative terms. Given that higher-revenue pharmacies typically have larger absolute sales, the impact in absolute terms is even more pronounced. This can be visualized in Figure 2, which illustrates the absolute increase in remuneration for each decile, calculated based on the results in Table 2.

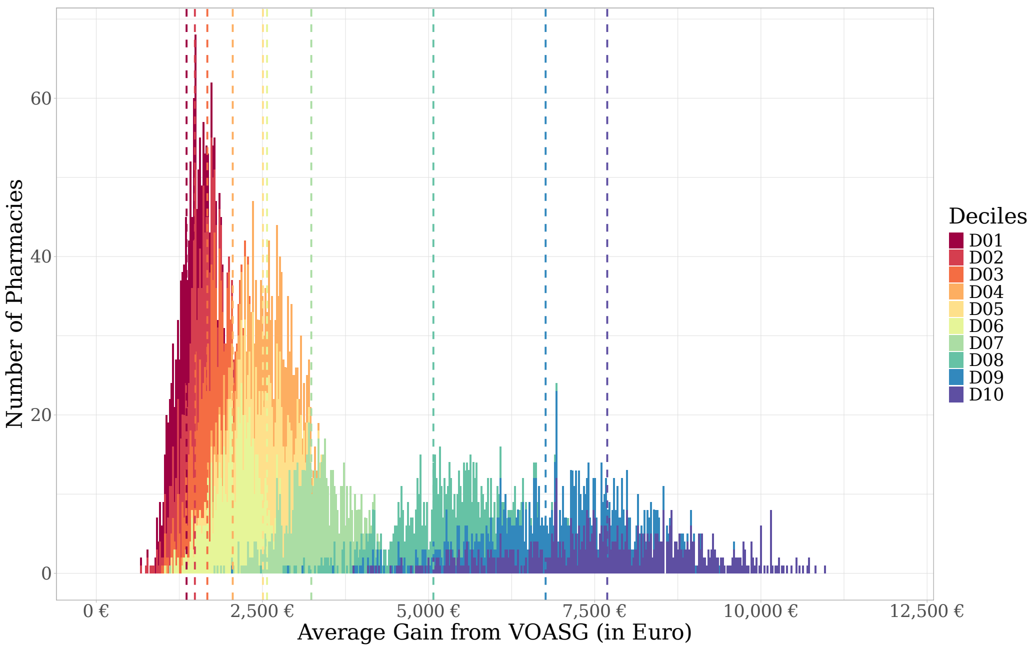

Figure 2: DiD effect for each decile (see Table 2). $Average\ Gain\ from\ VOASG = Sales \times \frac{\beta_{Decile}}{1+\beta_{Decile}} \times Average\ Remuneration\ Per\ Sale$.

Figure 2 illustrates the distribution of the absolute impact of the partial ban on rebates across pharmacies with varying revenue levels. This figure was constructed by multiplying each pharmacy's remuneration for dispensing Rx drugs by its corresponding DiD effect (see Table 2). For instance, the Rx remuneration of the pharmacy in the lowest revenue decile is multiplied by the "DiD for Decile 1", while the remuneration of the highest-revenue pharmacy is multiplied by the "DiD for Decile 10". (For a more detailed explanation of how remuneration is computed, see Appendix C.2.)

The dotted lines in Figure 2 represent the average increase in profits for each decile. As previously discussed, the first seven deciles exhibit significantly lower gains compared to the highest three. Our findings suggest that, on average, the rebate ban generated additional annual profits for pharmacies in the first decile of around €1,360. In contrast, the corresponding gain for pharmacies in the tenth decile is more than five times greater, reaching €7,690. Figure 2 also indicates that 50 % of the pharmacies experienced an increase in profits of less than €3,246 (median). In contrast, the average gain across all pharmacies is at 3,500. These results show that the gains from the introduction of VOASG were unevenly distributed across pharmacies, with *larger* pharmacies actually benefiting more strongly.

These results can be further contextualized. As discussed previously, pharmacies exit the market when opportunity costs exceed revenues. The question, therefore, is whether the additional profits are meaningful enough to sustain pharmacies in the market. To evaluate this, consider that the average *monthly* income of a German employee in 2021 was €4,100 (Destatis, `https://t.ly/N2dJq`). In contrast, the *annual* gain for pharmacies in the first decile approximates one-third of this amount. The majority of pharmacies experienced an increase equivalent to 50-60% of this figure. In other words, pharmacy owners' yearly gains were substantially less than the average monthly wage of an employee. Given that these owners are highly skilled professionals, the impact of the VOASG on their revenues can be considered relatively low.

Against the backdrop of these findings, the continued decline in the number of brick-and-mortar pharmacies after 2020 is unsurprising. By the end of 2023, the total number had decreased to 17,571, reflecting a 6.3 % reduction compared to 2020. While external factors, such as the war in Ukraine and the pandemic, influenced the market, the policy change appears to have failed to address the underlying causes of pharmacy closures.

4.2 Limitations

Our study is subject to certain limitations. While it relies on the most comprehensive and detailed dataset available on the German pharmacy market (to our knowledge), the data is limited to the 2-digit zip code level. Consequently, we are unable to further specify the precise location of a given pharmacy. If the data were more granular, we could have conditioned the effects on specific socio-geographic factors, such as rural versus urban areas and the specific competitive landscape of offline pharmacies.

A comparable dataset encompassing online sales is currently unavailable. Our interpretation, which posits that e-commerce experiences losses equivalent to the gains of the offline channel, is thus contingent on the assumption of inelastic demand.

It is essential to consider these limitations when interpreting our findings. However, these caveats do not affect the validity of our identification strategy.

5 Conclusion

Our study investigated the impact of a partial ban on rebates for prescription drugs (VOASG) on the German pharmacy market. We found that the ban led to a modest increase in offline sales (1.36-1.65 %) for brick-and-mortar pharmacies, likely at the expense of online sales. This suggests that a notable portion of consumers is price-sensitive for Rx drugs and will switch channels for cheaper options.

However, the policy appears to have had an asymmetric effect on pharmacies. We estimated that annual additional profits ranged from €1,360 - €7,690, with a median increase of €3,246. Pharmacies in the top three revenue deciles experienced a 40-140 % stronger sales increase compared to smaller ones.

This observation, coupled with the continued market exit observed after 2021 (6.3 % closure rate), suggests that further reforms are necessary to reverse the trend of declining pharmacy numbers. Such reforms can, for instance, specifically target pharmacy remuneration for dispensing Rx drugs.

Acknowledgements

The data used in our study was provided by the German suppliers of merchandise information systems (MIS): AWINTA, ADG and Pharmatechnik. We received funding from the Pharmacists Association Westfalen-Lippe (Apothekerverband Westfalen-Lippe e. V.) to buy the data.

Funding

The Pharmacists Association Westfalen-Lippe (AVWL) and pharmacists' cooperative NOWEDA are funding a research project at the Chair of Georg Götz. Our study is a product of this project. The project itself was scientific in nature (i. e., no commercial research project). To conduct this project, the positions of the co-authors Jan Thomas Schäfer and Daniel Herold were funded by the aforementioned parties.

Declarations of interest

The authors declare that they have no conflict of interest. This research was funded by AVWL and NOWEDA. The funding supported researcher positions, but the authors were granted full scientific freedom to conduct their research without any influence on the results or conclusions.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used OpenAI ChatGPT, Google Gemini and Writefull in order to improve language and GitHub Copilot in order to make coding more efficient. After using these services, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

CRediT (Contributor Roles Taxonomy)

Maximilian Maurice Gail: Conceptualization, Data curation, Formal analysis, Methodology, Software, Visualization, Writing - original draft, Writing – review and editing; **Georg Götz**: Conceptualization, Funding acquisition, Methodology, Project administration, Supervision, Validation, Writing – review and editing; **Daniel Herold**: Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Supervision, Validation, Writing - original draft, Writing – review and editing; **Jan Schäfer**: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review and editing

References

ABDA, 2021. Zahlen, daten, fakten 2021. `https://www.pharma4u.de/fileadmin/user_upload/pdf/ABDA-Leitlinien/ABDA_ZDF_2021_Broschuere.pdf`.

ABDA, 2024. Zahlen, daten, fakten 2024. `https://www.abda.de/fileadmin/user_upload/assets/ZDF/Zahlen-Daten-Fakten-24/ABDA_ZDF_2024_Broschuere.pdf`.

Agomo, C.O., 2012. The role of community pharmacists in public health: a scoping review of the literature. Journal of Pharmaceutical Health Services Research 3, 25–33.

Albrecht, M., Baake, P., an der Heiden, I., Brenck, A., Ochmann, R., Schiffhorst, G., 2020. Ökonomisches Gutachten zum Apothekenmarkt. Technical Report. IGES Institut und Deutsches Institut.

Brown, J.R., Goolsbee, A., 2002. Does the internet make markets more competitive? evidence from the life insurance industry. Journal of political economy 110, 481–507.

Brynjolfsson, E., Smith, M.D., 2000. Frictionless commerce? a comparison of internet and conventional retailers. Management science 46, 563–585.

Cavallo, A., 2017. Are online and offline prices similar? evidence from large multi-channel retailers. American Economic Review 107, 283–303.

Coenen, M., Haucap, J., Herr, A., Kuchinke, B., 2011. Wettbewerbspotenziale im deutschen Apothekenmarkt. Technical Report. DICE - Ordnungspolitische Perspektiven Nr. 17.

Costa, S., Cary, M., Helling, D.K., Pereira, J., Mateus, C., 2019. An overview of systematic reviews of economic evaluations of pharmacy-based public health interventions: addressing methodological challenges. Systematic reviews 8, 1–20.

Couture, V., Faber, B., Gu, Y., Liu, L., 2021. Connecting the countryside via e-commerce: evidence from china. American Economic Review: Insights 3, 35–50.

Cunningham, S., 2021. Causal inference: The mixtape. Yale university press.

Duminy, L., Ress, V., Wild, E.M., 2022. Complex community health and social care interventions–which features lead to reductions in hospitalizations for ambulatory care sensitive conditions? a systematic literature review. Health Policy 126, 1206–1225.

Elzinga, K.G., Mills, D.E., 2008. The economics of resale price maintenance. Issues in Competition Law and Policy (3-Volume Set), Kenneth G. Elzinga & David E. Mills, eds., ABA Section of Antitrust Law .

Freyaldenhoven, S., Hansen, C., Shapiro, J.M., 2019. Pre-event trends in the panel event-study design. American Economic Review 109, 3307–38.

Gatwood, J., Gibson, T.B., Chernew, M.E., Farr, A.M., Vogtmann, E., Fendrick, A.M., 2014. Price elasticity and medication use: cost sharing across multiple clinical conditions. Journal of Managed Care Pharmacy 20, 1102–1107.

Goldmanis, M., Hortaçsu, A., Syverson, C., Emre, Ö., 2010. E-commerce and the market structure of retail industries. The Economic Journal 120, 651–682.

Haschka, R.E., Schley, K., Herwartz, H., 2020. Provision of health care services and regional diversity in germany: Insights from a bayesian health frontier analysis with spatial dependencies. The European Journal of Health Economics 21, 55–71.

an der Heiden, I., Meyrahn, F., 2017. Ermittlung der Erforderlichkeit und des Ausmaßes der in der Arzneimittelpreisverordnung (AMPreisV) geregelten

Preise. Technical Report. 2HM & Associates GmbH. URL: https://www.bmwi.de/Redaktion/DE/Publikationen/Studien/ermittlung-der-erforderlichkeit-und-des-ausmasses-von-aenderungen-der-in-der-arzneimittelpreisverordnung.pdf?__blob=publicationFile&v=12.

Herwartz, H., Schley, K., 2018. Improving health care service provision by adapting to regional diversity: an efficiency analysis for the case of germany. Health Policy 122, 293–300.

Hunold, M., Muthers, J., 2017. Resale price maintenance and manufacturer competition for retail services. The RAND Journal of Economics 48, 3–23.

Inoue, Y., Takikawa, M., Morita, Y., Takao, K., Kanamoto, I., Sugibayashi, K., 2016. A comparison of pharmacists' role functions across various nations: the importance of screening. Research in Social and Administrative Pharmacy 12, 347–354.

Iyamu, I., Gómez-Ramírez, O., Xu, A.X., Chang, H.J., Watt, S., Mckee, G., Gilbert, M., 2022. Challenges in the development of digital public health interventions and mapped solutions: findings from a scoping review. Digital health 8, 20552076221102255.

Jehle, G., Reny, P., 2011. Advanced microeconomic theory, 3rd edition. Pearson Education Limited.

Jin, G.Z., Kato, A., 2007. Dividing online and offline: A case study. The review of economic studies 74, 981–1004.

Li, L., Liu, Z., 2021. Research on efficiency measurement and spatiotemporal disparity of rural public health services in china. PLoS One 16, e0252871.

Marvel, H.P., McCafferty, S., 1985. The welfare effects of resale price maintenance. The Journal of Law and Economics 28, 363–379.

Mays, G.P., Smith, S.A., Ingram, R.C., Racster, L.J., Lamberth, C.D., Lovely, E.S., 2009. Public health delivery systems: evidence, uncertainty, and emerging research needs. American Journal of Preventive Medicine 36, 256–265.

OECD, 2023. Health at a Glance. Technical Report. Organisation for Economic Co-operation and Development.

Perraudin, C., Bugnon, O., Pelletier-Fleury, N., 2016. Expanding professional pharmacy services in european community setting: is it cost-effective? a systematic review for health policy considerations. Health policy 120, 1350–1362.

Raza, M.A., Aziz, S., Noreen, M., Anjum, I., Raza, S.M., 2022. A portrait of the pharmacy profession globally: pharmacist universal professional identity and establishment of global pharmacy council. INNOVATIONS in pharmacy 13.

Roth, J., Sant'Anna, P.H., Bilinski, A., Poe, J., 2023. What's trending in difference-in-differences? a synthesis of the recent econometrics literature. Journal of Econometrics 235, 2218–2244.

Sinai, T., Waldfogel, J., 2004. Geography and the internet: Is the internet a substitute or a complement for cities? Journal of Urban Economics 56, 1–24.

Smith, F., 2009. Private local pharmacies in low-and middle-income countries: a review of interventions to enhance their role in public health. Tropical Medicine & International Health 14, 362–372.

Statista, 2024. Absatzanteile des arzneimittelversandhandels am deutschen otc-markt nach produktkategorie in den jahren 2008 bis 2019. https://de.statista.com/statistik/daten/studie/280477/umfrage/absatzanteile-am-otc-versandapothekenmarkt/.

Telser, L.G., 1960. Why should manufacturers want fair trade? The journal of law and economics 3, 86–105.

Wambach, A., Kollmann, D., Nöcker, T., Kühling, J., Westerwelle, A., 2018. Sondergutachten 80 – Die Buchpreisbindung in einem sich änderndem Marktumfeld. Technical Report. German Monopolies Commission.

WHO Collaborating Centre for Drug Statistics Methodology, 2024. Guidelines for ATC Classification and DDD Assignment. Oslo. URL: https://atcddd.fhi.no/atc_ddd_index_and_guidelines/guidelines/. last updated: 2024-03-01.

Wong, B.L.H., Maaß, L., Vodden, A., van Kessel, R., Sorbello, S., Buttigieg, S., Odone, A., 2022. The dawn of digital public health in europe: Implications for public health policy and practice. The Lancet Regional Health–Europe 14.

Yeung, K., Basu, A., Hansen, R.N., Sullivan, S.D., 2018. Price elasticities of pharmaceuticals in a value based-formulary setting. Health economics 27, 1788–1804.

Yurkovich, J.T., Evans, S.J., Rappaport, N., Boore, J.L., Lovejoy, J.C., Price, N.D., Hood, L.E., 2024. The transition from genomics to phenomics in personalized population health. Nature Reviews Genetics 25, 286–302.

A Appendix to Section "Methods"

A.1 Reimbursement for Prescription Drugs in Germany

In Germany, most residents are mandated to hold health insurance (Federal Ministry of Health, `https://t.ly/8Ev6L`). This system offers two primary options: statutory health insurance ("Gesetzliche Krankenversicherung", GKV) and private health insurance ("Private Krankenversicherung", PKV). As of 2021, around 73.3 Mio. and 8.7 Mio. citizens were members of the statutory and private health insurance scheme, respectively (Statista, `https://t.ly/pyzwt`). Rx drugs are prescribed by physicians and dispensed by both traditional and online pharmacies. This holds irrespective of the patients' insurance. Reimbursement, however, differs between statutory and private health insurance.

Members of the statutory health insurance are typically required to make co-payments, contributing a portion of the drug's cost. These co-payments are calculated based on the AVP. If the AVP is ...

- ... below EUR 5 the co-payment equals the AVP,
- ... between EUR 5 and EUR 50 the co-payment equals EUR 5,
- ... between EUR 50 and EUR 100 the co-payment equals 10% of the AVP,
- ... above EUR 100 the co-payment is capped at EUR 10.

Further payments beyond the aforementioned co-payments are possible, which depend on rebates between the consumers' insurance company and the drug manufacturers. These rebates fluctuate frequently, often on a quarterly basis, and systematic data on their exact amounts is generally unavailable. The remaining difference between the price of a prescribed drug and the co-payment and any applicable rebates is typically covered by the insurance provider.

Privately insured individuals can select from a range of insurance contracts, each offering distinct reimbursement structures. Typically, these schemes require patients to initially cover costs out-of-pocket, followed by reimbursement from the insurance provider upon submission of invoices. Contracts can be customized to accommodate individual needs, such as making exceptions for high-cost hospitalizations.

A.2 Data Handling and Preprocessing

The data were obtained from three major German suppliers of merchandise information systems (MIS): AWINTA (https://www.awinta.de), ADG (https://www.adg.de) and Pharmatechnik (https://www.pharmatechnik.de). These MIS oversee the entire system of inventory management and provide both hardware and software solutions to pharmacies, essentially handling the IT infrastructure. As a result, our data includes each transaction conducted by a pharmacist with a customer, excluding specialty drugs (e.g. cytostatics).

The dataset encompasses transactions of approximately 9,231 offline pharmacies, covering nearly half of all pharmacies in Germany. The data capture individual sales transactions from January 1, 2018, to October 31, 2022.

Further, essential details like AVP, transaction revenue, patient co-payments, and the central pharmaceutical number (PCN) that uniquely identifies each product are available or can be concluded from the data. Anonymized pharmacy identifiers are provided at a 2-digit zip code level. This represents the highest level of granularity attainable without compromising data privacy.

Using AVP, we can also calculate the wholesale price ("Apothekeneinkaufspreis", AEP) for each product, which allows us to compute the total remuneration pharmacies receive from RX-drugs. This calculation provides the basis for assessing the pharmacies' income from regulated drug sales (see Appendix C.2 for more details on the remuneration calculation).

To account for variations in package sizes, we use the German N-classification system established by the Federal Institute for Drugs and Medical Devices (https://www.bfarm.de/DE/Arzneimittel/Arzneimittelinformationen/Packungsgroessen/_node.html). This system categorizes pharmaceutical packages into three size classes based on estimated daily doses: N1 (approximately 10 days), N2 (approximately 30 days), and N3 (approximately 100 days). Given the limited availability of the usual "daily defined doses" (DDD) scheme for the PCN-level in our data set (see WHO Collaborating Centre for Drug Statistics Methodology (2024) and https://atcddd.fhi.no/ddd/definition_and_general_considera/ on the DDD-scheme), the N-classification system provides a workable alternative for comparing package sizes. In relation to DDD-scheme, we refer to the normalization based on the N-classification scheme as NDD in this Appendix.

The classifications were obtained from IQVIA, which provides standardized package size information for many PCNs. However, to ensure broader coverage, we also integrated publicly available data from the largest German health insurance *Techniker Krankenkasse* (https://www.tk.de/resource

/blob/2058850/3f65533a18b118a9ebcf585ef2830c40/rabattvertraege-pzn-liste-gesamt-data.pdf).

Data on the evolution of health insurance memberships are obtained from the Federal Ministry of Health (https://www.bundesgesundheitsministerium.de/themen/krankenversicherung/zahlen-und-fakten-zur-krankenversicherung/mitglieder-und-versicherte) and the Association of Private Health Insurance (https://www.pkv-zahlenportal.de/werte/2012/2022/12/pers-kkv/basket/result).

Our analysis utilizes annual data aggregated into two datasets: one at the 2-digit zip code level and another at the individual pharmacy level. Data for 2022 was excluded due to incompleteness. We focused on data for prescription drugs (excluding COVID-19 vaccines, prescribed masks, and specialty medications) pre-filtered by MIS suppliers. Using the dictionary *Gelbe Liste Pharmaindex* (https://www.gelbe-liste.de/), we further excluded non-pharmaceutical items like medical devices. The analysis only considers direct drug dispenses to customers, excluding sales via courier services and to nursing homes.

To ensure data consistency, we limited the analysis to standardized package sizes (N1, N2, and N3 categories) mandated by statutory health insurance. We balanced and pruned the data to exclude inactive pharmacies, those with minimal sales, or those specializing in expensive medications. Additionally, to minimize the influence of outliers, we removed the top and bottom 2.5% of pharmacies based on sales and remuneration distributions

B Appendix to Section "Results"

B.1 Descriptive Statistics

This section provides more detailed information on the geographical coverage of our sample, a graphical analysis of the DiD effect and the usual summary statistics.

Figure B.1 visually depicts the geographic scope of pharmacy sales data across Germany. The left panel illustrates the overall sample coverage, encompassing 9,231 unique pharmacies out of a total of 18,839 (49 %). The right panel zooms in on the coverage of the final sample, which comprises 5,487 pharmacies (29 %). Color intensity within each region corresponds to the percentage of coverage, with darker shades signifying higher data representation. A comparison of both panels reveals that, despite data balancing and processing, our sample retains coverage across all 2-digit zip codes in Germany, with a median coverage of approximately 29 % per 2-digit zip code.

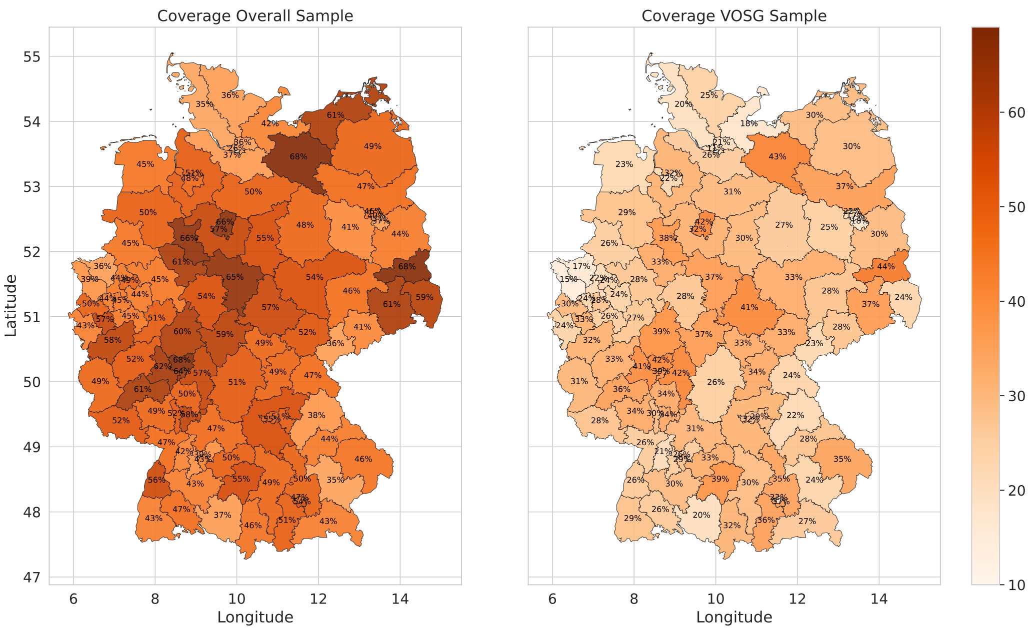

Figure B.1: Coverage of Pharmacy Sales Data Across German Regions. Source: MIS suppliers and web page of *Apothekenumschau* (`https://www.apotheken-umschau.de/apothekenfinder/`), scraped on September 29, 2020.

Figure B.2 depicts the annual sales trends in packages and NDD (see Section A.2), categorized by statutory health and private prescriptions. It comprises four subfigures: the top ones show absolute values, while the bottom ones display sales normalized to 2020. Figure B.2 reveals two key points.

Based on the figure, one can see that prescriptions issued to members of statutory health insurance are six times higher than those issued to privately insured and self-pay patients. This discrepancy is explained by the fact that most Germans are covered by statutory health insurance (see Appendix A.1).

We can also calculate a DiD effect by aggregating our data in years and by statutory health and private prescriptions without any covariates. That way, we find an effect of the VOASG in packages (NDD) of approximately 0.0163 (0.0113). Accordingly, by comparing means we find that sales of offline channels increased by 1.63 % (1.13 %) due to VOASG, compared to a counterfactual of a state without VOASG. This result should be viewed as a first indication. It is refined using a more sophisticated approach (see Section 3 and B.2).

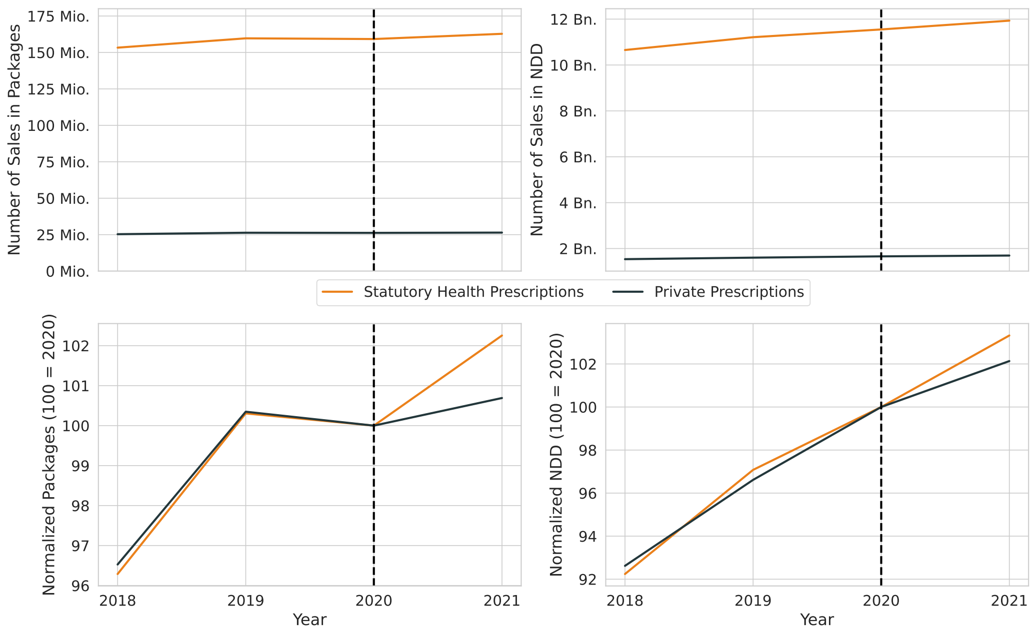

Figure B.2: Evolution of sales in packages and NDD by statutory health and private prescriptions. The top figures denote sales in absolute values, while the bottom figures depict sales normalized to the year 2020.

Tables B.1 and B.2 report summary statistics at the 2-digit zip code and pharmacy levels, respectively, differentiated between private and statutory health prescriptions.

	Private Prescriptions						Statutory Health Prescriptions					
	N	Mean	SD	Min	Median	Max	N	Mean	SD	Min	Median	Max
Sales per 2-digit-zip code and Year in Packages	380	274,393	126,162	33,328	274,106	709,750	380	1,670,946	647,546	177,155	1,594,334	3,948,482
Sales per 2-digit-zip code and Year in NDD	380	17,088,357	7,877,312	1,958,510	16,797,645	46,334,170	380	1.19e + 08	47,241,362	11,561,710	1.16e + 08	3.06e + 08
Gross Revenue per 2-digit-zip code and Year in Euro	380	14,668,064	6,949,777	1,775,727	14,312,372	39,087,452	380	93,061,340	36,210,488	11,564,190	92,083,137	2.39e + 08
Net Revenue per 2-digit-zip code and Year in Euro	380	12,366,244	5,861,491	1,492,210	12,104,528	32,847,140	380	78,456,469	30,537,605	9,717,812	77,561,420	2.01e + 08
Net Revenue (w.o. lump sum fees) per 2-digit-zip code and Year in Euro	380	12,314,791	5,837,464	1,486,483	12,050,517	32,691,821	380	75,653,612	29,463,615	9,425,507	7.5e + 07	1.94e + 08
Total Remuneration per 2-digit-zip code and Year in Euro	380	2,583,160	1,191,630	315,717	2,574,276	6,706,106	380	13,332,543	5,159,417	1,454,439	12,815,406	31,943,711
Average Remuneration per 2-digit-zip code and Year in Euro	380	9.4	0.084	9.15	9.41	9.71	380	7.98	0.0927	7.77	7.97	8.33
Gross AVP per 2-digit-zip code and Year in Euro/Package	380	53	3.38	42.7	53.1	65.7	380	55.9	3.75	47.2	55.5	69.3
Net AVP per 2-digit-zip code and Year in Euro/Package	380	44.7	2.89	35.9	44.8	55.2	380	47.1	3.19	39.7	46.8	59
Number of Pharmacies per 2 digit zip-code	380	57.8	21.8	9	54	121	380	57.8	21.8	9	54	121
Quantity weighted average NDD	380	62.2	2.61	54.2	62.4	68.2	380	71.3	3.06	64	71	78.8

Table B.1: Summary statistics on the 2-digit-zip code sample. 760 observations in total.

	Private Prescriptions						Statutory Health Prescriptions					
	N	Mean	SD	Min	Median	Max	N	Mean	SD	Min	Median	Max
Sales per Pharmacy and Year in Packages	21948	4,751	2,685	385	4,162	25,207	21948	28,930	12,278	6,591	26,688	74,147
Sales per Pharmacy and Year in NDD	21948	295,862	167,431	22,640	259,715	1,530,590	21948	2,066,169	912,123	385,530	1,907,845	5,777,330
Gross Revenue per Pharmacy and Year in Euro	21948	253,958	170,740	12,770	213,515	2,359,418	21948	1,611,232	763,634	313,249	1,458,762	7,044,259
Net Revenue per Pharmacy and Year in Euro	21948	214,105	143,972	10,731	180,068	1,982,707	21948	1,358,368	643,953	263,235	1,228,696	5,919,541
Net Revenue (w.o. lump sum fees) per Pharmacy and Year in Euro	21948	213,214	143,510	10,636	179,253	1,981,299	21948	1,309,840	625,601	251,675	1,183,001	5,820,396
Total Remuneration per Pharmacy and Year in Euro	21948	44,724	25,607	3,605	39,117	242,996	21948	230,835	98,256	51,762	212,854	594,033
Average Remuneration per Pharmacy and Year in Euro	21948	9.39	0.385	8.62	9.32	24.1	21948	7.98	0.279	7.41	7.92	9.84
Gross AVP per Pharmacy and Year in Euro/Package	21948	52.4	15.7	21.3	49.7	652	21948	55.8	11.3	32.5	53.4	132
Net AVP per Pharmacy and Year in Euro/Package	21948	44.2	13.2	17.9	41.9	548	21948	47.1	9.57	27.3	45	111
Quantity weighted average NDD	21948	62.3	5.16	30	62.8	78.7	21948	71.1	5.64	36	71.7	85

Table B.2: Summary statistics on the pharmacy level sample. 43,896 observations in total.

The descriptive statistics include the number of observations (N), mean, standard deviation (SD), median, minimum, and maximum for annual sales in packages or NDD, gross revenue, net revenue, net revenue excluding lump sum fees, total remuneration, quantity weighted average NDD, average remuneration, and both gross and net AVP, presented separately for 2-digit zip codes and pharmacies. These sales figures represent the main variables of interest in our estimations, while the other variables are used to calculate distributional effects in Section 4.1.

B.2 DiD-Estimation

The causal effect of the VOASG is examined through a TWFE DiD estimation in conjunction with an event study. The empirical model we estimate is given by

$$\ln(y_{pgt}) = \alpha_{pg} + \gamma_t + \beta D_{pgt} + W_{pgt}\mu + \epsilon_{pgt}, \tag{B.1}$$

where y denotes sales for pharmacies p and statutory health or private prescriptions g at time t (in years). The outcome variable y is measured in logs. D_{pgt} is an indicator variable that equals one if g represents a statutory health prescription at time $t = 2021$. Fixed effects α_{pg} and γ_t are included to capture cross-sectional heterogeneity for each combination of p and g, as well as time-varying effects. Therefore, β represents the DiD effect or ATT. Since the outcome variable is measured in logs, the coefficient β can be interpreted as a percentage change. The exact ATT is computed by $e^{\beta} - 1$, although this transformation is negligible when the effect is close to zero, as it is in our case.

The matrix $\boldsymbol{W}_{pgt}$ includes the following covariates: (i) the quantity-weighted average of doses (NDD) per pharmacy p and group g at time t, and (ii) the fraction of members in statutory health or private insurance at the national level. Covariate (i) accounts for potential temporal variations in package sizes between treatment and control groups. Covariate (ii) controls for potential changes in group sizes and technically has a similar effect as a time trend. Given collinearity between Covariate (ii) and a direct time trend, we cannot include both in a single model.

The results of the TWFE DiD estimation (B.1) are presented in Section 3, Table 1. The ATT varies between 0.0136 and 0.0165.

Alternatively, we can use NDD as the dependent variable in equation (B.1) instead of incorporating it as a covariate. This approach provides a robustness check for the estimates presented earlier. Table B.3 displays the results of this alternative estimation.

The table's interpretation and structure mirror those of Table 1. The ATT reported in Table B.3 are comparable to those in the main text, ranging from 0.0139 to 0.0158.

B.3 Event Study

The estimation equation for the event study presented in Section 3 reads as follows:

$$\ln(y_{pgt}) = \alpha_{pg} + \gamma_t + \sum_{\tau=2018}^{2020} \delta_\tau D_{pg\tau} + \beta_{2021} D_{pg2021} + W_{pgt}\mu + \epsilon_{pgt}. \qquad \text{(B.2)}$$

The model includes the years 2018, 2019 and 2020 as leads and the year 2021 as a lag, denoted by δ_{2018}, δ_{2019}, δ_{2020}, and β_{2021}, respectively. As is standard in the literature (see Cunningham (2021, Chapter 9.4) or Freyalden-

	(1)	(2)	(3)	(4)
Specification A: Sales in NDD				
DiD-Coefficient	0.0139***	0.0150***	0.0150***	0.0150***
	(0.0038)	(0.0023)	(0.0015)	(0.0031)
Fraction of Members in Insurance	-1.9188	-2.1932*	-2.1932*	-2.1932
	(1.8371)	(1.2062)	(1.1068)	(1.6978)
Weighted Average of Doses	0.0172***	0.0156***	0.0156***	0.0156***
	(0.0029)	(0.0006)	(0.0008)	(0.0008)
Observations	760	43,896	43,896	43,896
Adj. R2	0.9998	0.9945	0.9945	0.9945
FE: Year	X	X	X	X
FE: 2 digit zip code & Treated	X			
FE: Pharmacy & Treated		X	X	X
Std. Errors	Robust	Robust	by: 2-digit-zip code	by: 2-digit-zip code & Treated
Specification B: Sales in NDD with Trends				
DiD-Coefficient	0.0145***	0.0158***	0.0158***	0.0158***
	(0.0047)	(0.0028)	(0.0018)	(0.0036)
Weighted Average of Doses	0.0171***	0.0156***	0.0156***	0.0156***
	(0.0030)	(0.0006)	(0.0008)	(0.0008)
Time Trend of Treatment-Group	-0.0013	-0.0015	-0.0015	-0.0015
	(0.0017)	(0.0011)	(0.0010)	(0.0015)
Observations	760	43,896	43,896	43,896
Adj. R2	0.9998	0.9945	0.9945	0.9945
FE: Year	X	X	X	X
FE: 2 digit zip code & Treated	X			
FE: Pharmacy & Treated		X	X	X
Std. Errors	Robust	Robust	by: 2-digit-zip code	by: 2-digit-zip code & Treated

Note:
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.3: TWFE DiD estimation with NDD as dependent variable.

hoven et al. (2019)), the event study is normalized to the pre-intervention period (2020). (Note that it is technically impossible to include a time trend or Covariate (ii) as introduced in Section B.2 into an event study as it would be collinear with the leads and lags.) The coefficient β_{2021} in Equation (B.2) can be interpreted in a similar way as the ATT, because there is only one post-treatment period. The coefficients $\delta_\tau \in \{2018, 2019, 2020\}$ capture the pre-treatment effects, which allow us to examine dynamics prior to the policy intervention.

The pre-treatment coefficients, δ_{2018} and δ_{2019}, can be used to assess the parallel trends assumption before the treatment. Based on the literature (Roth et al., 2023, Sections 4.3–4.4), parallel trends are plausible when pre-treatment coefficients are statistically insignificant. Figure 1 in the main Text and Table B.4 below shows that this holds for all lags.

	(1)	(2)	(3)	(4)
Lead 2018	-0.0035	-0.0026	-0.0026	-0.0026
	(0.0035)	(0.0022)	(0.0021)	(0.0030)
Lead 2019	0.0011	0.0023	0.0023*	0.0023
	(0.0026)	(0.0016)	(0.0012)	(0.0021)
Lag 2021	0.0162***	0.0174***	0.0174***	0.0174***
	(0.0039)	(0.0023)	(0.0014)	(0.0031)
Weighted Average of Doses	0.0009	-0.0006	-0.0006	-0.0006
	(0.0031)	(0.0006)	(0.0009)	(0.0008)
Observations	760	43,896	43,896	43,896
Adj. R2	0.9997	0.9938	0.9938	0.9938
FE: Year	X	X	X	X
FE: 2 digit zip code & Treated	X			
FE: Pharmacy & Treated		X	X	X
Std. Errors	Robust	Robust	by: 2-digit-zip code	by: 2-digit-zip code & Treated

Note:
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.4: Estimation results for Equation (B.2)).

C Appendix to Section "Discussion"

C.1 DiD with Deciles

To estimate how the effects of the VOASG differ between pharmacies with different revenues, the DiD coefficient D_{gt} is interacted with a dummy variable $Deciles_{pgt}$ that categorizes pharmacies into deciles based on their total revenue:

$$ln(y_{pgt}) = \alpha_{pg} + \gamma_t + Deciles_{pgt} + Deciles_{pgt} \times D_{pgt} + W_{pgt}\mu + \epsilon_{pgt}. \quad \text{(C.1)}$$

Equation (C.1) closely resembles Equation (B.1). The dummy $Deciles_{pgt}$ accounts for decile-specific heterogeneity. (Note that $Deciles_{pgt}$ is not collinear with the fixed effect α_{pg} as pharmacies can shift between deciles over time). This approach addresses unobserved heterogeneity.

C.2 Remuneration

In this section, we describe how pharmacies' remuneration is computed. This is a prerequisite step to quantify the absolute gains caused by the introduction of VOASG in the following section.

The remuneration structure for pharmacies dispensing prescription medications in Germany is subject to stringent regulatory oversight. Pharmacists are currently compensated with a fixed fee of € 8.35 per package, in addition to a variable component that constitutes 3 % of the AEP (§ 3 AMPreisV). For prescriptions covered by statutory health insurance, pharmacies are required to deduct an additional gross lump-sum fee of € 1.77 (§ 130 (1) SGB V), provided the insurance pays within 10 days. In net terms, this results in a deduction of € 1.49 per package.

This remuneration framework applies exclusively to *Fertigarzneimittel* (finished dosage form, § 4 (1) sentence 2 German Medicines Act, AMG), which is the only category included in our dataset. The following computation, based on AVP, will clarify how the remuneration is calculated, as our analysis focuses solely on AVP for prescription drugs.

The remuneration for pharmacies can be computed based on AVP, as it represents a list price that follows a consistent pattern:

$$(Gross)\ AVP = (1 + \text{VAT}) \cdot (Net)\ AVP \tag{C.2}$$

$$(Net)\ AVP = r_f + r_v + pDL + nDZ + AEP. \tag{C.3}$$

As shown in Equation (C.2), gross AVP is calculated by multiplying net AVP by the value-added tax rate, which is 19% in Germany (16% for the first two quarters of 2020). Net AVP, Equation (C.3), consists of a fixed rate, $r_f =$ € 8.35, in addition to a variable component, $r_v = 0.03 \cdot AEP$. Recall that AEP refers to the wholesale price. Moreover, AVP includes two lump-sum fees per prescription drug in net terms: the *pharmazeutische Dienstleistung* (pDL) fee, $pDL =$ € 0.20, and the *Notdienstzuschlag* (nDZ) fee, $nDZ =$ € 0.20 (for more details, refer to `https://www.abda.de/apotheke-in-deutschland/preise-und-honorare/beispielrechnung/`). By rearranging the terms of Equation (C.3), we can derive AEP:

$$AEP = \frac{(Net)\ AVP - (r_f + pDL + nDZ)}{1.03}. \tag{C.4}$$

Based on AEP, we can compute the compensation per Rx-drug dispensed:

$$\begin{aligned} R(AEP) &= \underbrace{(Net)\ AVP - pDL - nDZ - STHF}_{(Net)\ AVP \text{ w.o. lump sum fees}} - AEP \\ &= r_f + r_v - STHF \\ &= € \ 8.35 + 0.03 \cdot AEP - € \ 1.49. \end{aligned} \tag{C.5}$$

Here, $STHF =$ € 1.49 denotes the additional net lump-sum fee per statutory health insurance prescription drug (with $STHF = 0$ for private prescriptions). For example, an Rx-drug prescribed under statutory health insurance with $AEP =$ € 50 results in a remuneration of $R(50) =$ € 8.36.

Regarding the technical implementation, during the aggregation process, we ascertain net revenue excluding elements pDL, nDZ, and $STHF$, denoted $(Net)\ AVP\ w.o.\ lump\ sum\ fees$. We also determine the total costs by summing over AEP and further differentiate these figures to derive the total remuneration for each 2-digit zip code or pharmacy p, group g, and year t (see Tables B.1 and B.2). The results of the respective calculations for deciles 1 to 10 are summarized in Table C.1.

	Deciles	Mean	SD	Min	P25	Median	P75	Max
Gross Revenue (in Euro) from Statutory Health Prescriptions by Pharmacy in 2021	D01	694,825	107,027	365,910	619,466	707,555	780,411	918,617
	D02	898,429	105,612	375,124	836,078	907,012	978,202	1,118,446
	D03	1,069,323	105,645	695,538	1,008,279	1,082,769	1,144,722	1,304,631
	D04	1,217,061	116,976	519,110	1,153,307	1,229,121	1,298,209	1,447,576
	D05	1,377,001	133,080	790,864	1,307,640	1,397,290	1,462,790	1,642,521
	D06	1,559,251	142,510	834,556	1,487,207	1,578,656	1,659,385	1,849,085
	D07	1,763,678	147,199	732,421	1,676,696	1,771,491	1,856,267	2,074,630
	D08	2,011,384	175,497	1,323,046	1,914,402	2,025,218	2,133,129	2,416,269
	D09	2,381,734	233,485	1,006,973	2,243,196	2,399,030	2,541,571	2,945,108
	D10	3,249,097	627,266	2,012,603	2,854,133	3,098,203	3,482,232	6,869,854
Net Revenue (in Euro) from Statutory Health Prescriptions by Pharmacy in 2021	D01	583,871	89,935	307,466	520,558	594,562	655,778	771,945
	D02	754,962	88,741	315,225	702,584	762,193	821,996	939,868
	D03	898,569	88,772	584,445	847,291	909,839	961,945	1,096,164
	D04	1,022,717	98,294	436,225	969,085	1,032,873	1,090,928	1,216,397
	D05	1,157,115	111,837	664,572	1,098,846	1,174,192	1,229,234	1,380,185
	D06	1,310,257	119,747	701,306	1,249,705	1,326,587	1,394,440	1,553,846
	D07	1,482,054	123,684	615,481	1,408,982	1,488,629	1,559,907	1,743,322
	D08	1,690,203	147,481	1,111,802	1,608,663	1,701,839	1,792,340	2,030,473
	D09	$2e+06$	196,206	846,196	1,885,031	2,015,969	2,135,773	2,474,939
	D10	2,730,298	527,110	1,691,216	2,398,426	2,603,527	2,926,157	5,772,980
Net Revenue w.o. lump sum fees (in Euro) from Statutory Health Prescriptions by Pharmacy in 2021	D01	560,415	87,060	295,819	498,801	568,880	628,475	740,249
	D02	725,822	85,601	301,853	677,522	732,485	789,090	906,640
	D03	864,615	85,838	556,555	814,771	875,090	926,494	1,060,352
	D04	984,163	95,004	420,673	932,825	992,887	1,051,264	1,175,963
	D05	1,114,338	108,121	646,402	1,056,123	1,130,154	1,183,478	1,347,118
	D06	1,262,126	115,626	677,613	1,202,639	1,277,625	1,339,810	1,504,633
	D07	1,428,648	120,700	597,998	1,357,673	1,435,713	1,507,907	1,689,007
	D08	1,629,473	142,867	1,070,758	1,547,803	1,643,388	1,729,281	1,966,905
	D09	1,930,876	189,985	826,700	1,817,743	1,944,083	2,058,881	2,393,400
	D10	2,644,192	520,429	1,630,590	2,316,601	2,516,686	2,841,886	5,664,327
Total Remuneration (in Euro) from Statutory Health Prescriptions by Pharmacy in 2021	D01	107,788	17,536	54,039	95,022	107,500	120,585	153,070
	D02	134,769	22,370	60,962	120,310	135,985	150,501	187,565
	D03	157,586	23,512	93,360	141,666	160,836	174,790	217,194
	D04	179,000	26,270	72,882	162,217	180,972	199,126	233,019
	D05	199,269	31,633	89,633	178,379	204,688	221,627	270,290
	D06	224,442	35,606	112,155	201,281	229,664	250,671	303,367
	D07	249,862	36,033	85,547	229,440	250,915	274,787	329,040
	D08	284,276	43,145	139,039	258,801	288,453	314,700	397,559
	D09	331,314	55,485	$1e+05$	298,599	335,423	372,308	470,201
	D10	412,801	75,463	207,936	367,546	412,764	465,584	588,611
Total Net Revenue (in Euro) per Pharmacy from Rx in 2021	D01	693,373	84,438	436,844	631,480	713,541	763,667	805,599
	D02	893,718	48,541	805,975	851,774	898,746	934,183	973,616
	D03	1,051,556	44,295	974,228	1,013,446	1,053,345	1,092,117	1,123,415
	D04	1,193,845	42,963	1,123,768	1,154,162	1,193,204	1,230,982	1,271,731
	D05	1,351,620	44,027	1,272,385	1,313,041	1,350,629	1,390,098	1,427,260
	D06	1,512,879	48,487	1,427,668	1,470,210	1,514,149	1,556,733	1,594,732
	D07	1,703,807	61,527	1,595,295	1,652,130	1,702,838	1,759,689	1,808,252
	D08	1,938,898	80,837	1,808,417	1,869,584	1,934,012	2,009,602	2,088,366
	D09	2,306,836	132,220	2,088,832	2,197,524	2,297,658	2,419,661	2,556,098
	D10	3,108,563	538,309	2,556,484	2,729,172	2,939,959	3,332,300	6,242,840
Sales (in Packages) of Statutory Health Prescriptions per Pharmacy in 2021	D01	13,733	2,350	6,820	11,952	13,624	15,402	19,821
	D02	17,060	3,132	7,833	14,927	17,239	19,288	24,610
	D03	19,879	3,330	10,348	17,666	20,220	22,196	28,623
	D04	22,572	3,723	9,103	20,151	22,780	25,439	30,227
	D05	25,046	4,516	10,631	21,999	25,777	28,296	35,292
	D06	28,179	5,102	13,402	24,852	28,706	31,961	39,949
	D07	31,267	5,227	10,229	28,200	31,482	34,974	42,797
	D08	35,556	6,199	15,360	31,834	36,198	39,817	52,179
	D09	41,300	7,939	11,428	36,436	41,830	46,890	61,203
	D10	50,415	10,298	23,148	43,717	51,290	57,808	73,556
Average Remuneration per Sale (in Euro) from Statutory Health Prescriptions by Pharmacy in 2021	D01	7.86	0.157	7.52	7.75	7.84	7.96	8.42
	D02	7.93	0.217	7.54	7.78	7.88	8.04	8.74
	D03	7.96	0.215	7.57	7.82	7.93	8.06	9.07
	D04	7.96	0.209	7.57	7.82	7.92	8.05	8.97
	D05	7.99	0.257	7.61	7.84	7.93	8.11	9.32
	D06	8	0.258	7.55	7.84	7.95	8.1	9.68
	D07	8.03	0.273	7.61	7.86	7.97	8.12	9.65
	D08	8.03	0.271	7.62	7.86	7.97	8.11	9.35
	D09	8.07	0.307	7.61	7.88	7.99	8.17	9.53
	D10	8.24	0.391	7.66	7.96	8.11	8.42	9.84

Table C.1: Summary statistics for the presented calculations by deciles 1 to 10.

C.3 Distributional Effects

In Section 4.1, particularly in Figure 2, we provided a histogram visualizing the "Average Gain from VOASG" for each pharmacy. This measure is derived from the DiD coefficient *for each decile*, the volume of sales from statutory health prescriptions, and the average remuneration per sale across pharmacies for the year 2021 (see Table C.1). The average remuneration per sale is calculated by dividing the total remuneration by the sales expressed in packages, thereby yielding a quantity-weighted average remuneration per package for each pharmacy p, group g, and year t.

Table C.2 displays summary statistics for the *Average gain from VOASG* by decile.

	Deciles	Mean	SD	Min	P25	Median	P75	Max
Average Gain from VOASG (in Euro) by $\beta_{Deciles}$	D01	1,359	221	681	1,198	1,355	1,520	1,929
	D02	1,484	246	671	1,325	1,498	1,657	2,066
	D03	1,671	249	990	1,502	1,706	1,854	2,303
	D04	2,569	377	1,046	2,328	2,598	2,858	3,345
	D05	2,508	398	1,128	2,245	2,576	2,789	3,401
	D06	2,053	326	1,026	1,841	2,101	2,293	2,775
	D07	3,236	467	1,108	2,971	3,249	3,558	4,261
	D08	5,072	770	2,481	4,618	5,147	5,615	7,094
	D09	6,761	1,132	2,045	6,093	6,845	7,597	9,595
	D10	7,688	1,405	3,872	6,845	7,687	8,671	10,962

Table C.2: Summary statistics for the *Average gain from VOASG* by decile.