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BEYOND THE CLOCK: EXPLORING THE CAUSAL RELATIONSHIP BETWEEN GENERAL PRACTITIONER TIME ALLOCATION AND HOSPITAL REFERRALS

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Beyond the Clock: Exploring the Causal Relationship between General Practitioner Time Allocation and Hospital Referrals

A Preprint

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Abstract

This paper presents an analysis of an experiment conducted in the Netherlands to evaluate the impact of a new way of working for General Practitioners (GPs) with respect to hospital referrals and healthcare spending. The new way of working gave GPs more time to spend on each patient, and we employed a Bayesian difference-in-differences approach to estimate the effect of this intervention. To assess the impact of the new way of working, we created a control group consisting of regional GP practices that did not implement the new approach and analyzed data on hospital referrals and healthcare spending in both the practice that implemented the new approach (the treatment practice) and the control group, both before and after the intervention. Our analysis shows that the new approach led to a substantial reduction in the total number of hospital referrals. We also observed a decrease in overall healthcare spending on combined GP and hospital care for the treatment practice relative to the control group.

***K*eywords** Primary care · Time allocation · Referrals · Health care cost · Difference in Differences design

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1 Introduction

In the Netherlands, general practitioners (GPs) function as gatekeepers for non-acute medical care. This means that patients require a referral from their GP in order to access specialist medical services. GPs in the Netherlands basically operate under a two-part tariff system whereby they receive a fee for each patient registered and a payment per visit. However, with over 2,000 patients registered per doctor, time constraints can make the gatekeeping role more challenging in practice, creating a potential conflict between financial incentives and optimum patient care. Normal GP consultations take ten minutes, with twenty minutes for a long consultation. In many cases, it can be quicker and easier for GPs to make a referral to a hospital or to prescribe medication than provide the most appropriate care to a particular patient.

In 2015, the GP practice in the Dutch town of Afferden introduced a different way of working. GPs were given more time to spend on each patient to find out in more detail what care they need and to discuss this with other the GPs in the practice. The approach the GP practice has implemented in their practice is characterized as 'Positive Health' and is described in Huber et al. (2022). The insurer VGZ and the GP practice provided information indicating that the GP practice had hired an additional GP to work two days a week in order to reduce the patient-to-GP ratio from 2,300 to around 1,800.

The primary objective of this intervention was to improve patient health outcomes, which in turn was expected to result in a decrease in the number of hospital referrals. A secondary goal of the intervention was, potentially, to reduce the number of drug prescriptions and diagnostic tests such as scans and blood tests, which GPs often rely on hospitals to perform.

In 2016, the new working method was reinforced through changes to GP remuneration. Before 2016, the GP practice in Afferden, like most Dutch GP practices, received a basic grant through a capitation system based on a fixed amount of money per person registered with the practice. The rest of their income was based on a fee-for-service principle, with a payment made for each patient consultation. As part of the intervention, a new payment scheme was negotiated between the GP practice and the main insurer, VGZ. Under the new scheme, the two-part tariff system based partly on capitation and partly on fee-for-service was replaced by payment for each person registered only, thus eliminating any financial incentive for GPs to increase the number of patient consultations.

In this paper, we study the causal relationship of remuneration and additional time for task completion on health outcomes. In more concrete terms, we examine how the removal of the financial 'pay-for-performance' incentive and the reduction of the number of patients per doctor affected hospital referrals and health costs in a GP practice in the Netherlands.

We believe that this research is important, because good healthcare systems play a core role in providing qualitative and inclusive treatment to a broad public. As societies age, healthcare systems are struggling to cope with the increasing demand for GP visits and services. Various studies have evaluated various policy solutions aimed at ensuring qualitative and affordable public healthcare. Our study evaluates an intervention that was implemented in a GP practice in the municipality of Afferden in the Netherlands starting in 2015, using a difference-in-differences approach. We found that flat-fee payments and allowing more time per patient reduced the number of hospital referrals and overall healthcare spending. Registered patients subject to the intervention were less likely to be referred to a hospital and were expected to face lower health care costs. Unfortunately, we were unable to analyze the impact of the intervention on health outcomes or the quality of care due to the lack of available data. We will discuss this limitation and its implications further in the discussion section.

Research designs that follow treatment subjects over time may suffer from treatment switching, which can bias study outcomes because individuals may migrate from the treatment group to the control group (Latimer et al. (2016)). However, the structure of the Dutch healthcare system ensures that patient migration is unlikely to affect the validity of the study: patients are required to be registered with a specific GP and could not easily switch to another practice because there are no other GP practices in Afferden. Additionally, other GPs were unlikely to accept patients from Afferden because this would have involved long distances and travel times for home visits. Patients can only be treated by the GP practice with whom they are registered. All this allows us to track the effect of individual enrollment clearly and, hence, the time available per patient compared to the number of hospital referrals.

GPs in many countries act as gatekeepers, ensuring appropriate access to specialist healthcare services. They act as an agent for the patient and play a critical role in coordinating care between different medical specialists and preventing the overutilization of services and unnecessary costs, bridging the information gap and promoting patient-centered care. In a systematic review, Sripa et al. (2019) show that gatekeeping was associated with lower healthcare utilization, better quality of care but also with lower patient satisfaction.

Our paper focuses on how much time GPs as gatekeeps dedicate to individual patients during consultations, and is in line with Freedman et al. (2021), who show that less one-on-one patient time reduces the number of subjects that physicians discuss with their patient during a visit and also the preventive care that they recommend. Tighter time limits increase the amount of planned and unplanned follow-up care.

The effect of doctor's time allocation on patient outcomes is also shown in other sectors. Andreyeva, David, and Song (2018) show that in the home healthcare sector in the US there is a negative relationship between the duration of health examinations and the probability of readmission in the post-acute care system.

A shift in incentives for GPs may result in changes to how they allocate their time to patients, highlighting the potential influence of reimbursement schemes. For example, Gaynor, Rebitzer, and Taylor (2004) show that high-powered incentives improve efficiency and reduce medical expenditure in a Health Maintenance Organizations (HMOs) by up to 5%.

While we studied a contract in which GPs receive a fixed subscription fee per patient, Hayen et al. (2021) examined the implementation of a shared savings contract in the Netherlands. They found that, in a similar setting, the first year of the shared savings arrangement resulted in a 2% decrease in per-capita medical spending. Notably, they also discovered that of the seven GPs examined, five exhibited cost-saving behavior.

2 Materials and method

2.1 Study population

We used health insurance claims data on hospital and GP care from 2012 to 2017 on all insured people in the Netherlands. The data came from Vektis, a private organization which collects data on behalf of all healthcare insurers in the Netherlands. We looked at patients who were registered at the GP practices in the intervention and control group between 2012 and 2017. The intervention starts in 2015. The study includes a total of four GP practices: one practice in Afferden formed the intervention group, and the remaining three practices formed the control group. The number of patients per practice included in the study was variable due to patients not being registered with the GP practices in either group for the whole study period.

The GP practice in Afferden is situated in a small town in a rural area. We asked the GP from the practice in Afferden for a comparable control group of GP practices nearby his GP practice. The GP suggested four GP practices that were willing to participate and answer questions on the interventions introduced in their GP practice, type of interventions and at what point in time between 2012 and 2017 they were introduced. One GP practice was excluded from the control group because it had undergone similar interventions to the GP practice in Afferden in 2015. The remaining three GP practices formed the final control group, and we were able to contact them for all our inquiries. All these GP practices are served by the same hospital, although it is not the closest hospital for the intervention group's GP practice. We excluded individuals for whom no data on hospital or GP spending was available.

2.2 Study variables

We were interested in everyone registered with the GP practices in the control and treatment groups in the years 2012 to 2017. Prior to the intervention, the GPs in the control and intervention groups were subject to a two-part tariff system, which provided an incentive to arrange more patient visits. We used individual claims data on all GP and hospital care which links every insured person in the Netherlands to a GP practice. To identify our sample, we obtained the list of all individuals registered with the four GP practices (both the intervention and control groups) during the first quarter of the years 2012 to 2017 from the GP claims data. We included all individuals who were registered with these practices during this period and examined their hospital referrals and insurance claims for GP and hospital care. Our analysis focused on the number of hospital care referrals per individual per year, which was the primary variable of interest. To identify referrals, we relied on claims data relating to hospital care, and specifically looked at claims for non-acute care that required an explicit referral from a provider of primary care such as a GP. Referrals to acute care were excluded, as we believe that GPs have limited influence over such cases.

The financial benefit of fewer referrals as a result of the intervention would be reduced spending on hospital care. We therefore also looked at individualized annual spending on hospital and GP care.

To account for patient characteristics, we assigned each individual in both the control and treatment groups to a risk-score decile. The risk score is a compact measure which incorporates multiple patient mix characteristics. It represents how much an individual's predicted healthcare costs deviate from the average predicted healthcare costs for all insured individuals in the Netherlands. We used expected healthcare costs from the national risk equalization model on somatic care (the result of multiplying characteristics in the model by the publicly available estimated parameter values of the model; see Ven et al. (2023) for an overview of the system and the risk factors). For each year, we calculated a risk score for each individual. Typically, a very low number of insured persons incurred major healthcare costs and a large number had costs of almost zero. This skewed distribution meant that if these costs could be expected on the basis of patient characteristics, insured persons with costs in the tail of the distribution would have a higher risk score, and insured persons with no costs would have a lower risk score. For every year, each insured person was placed in one of ten groups based on their risk score, with every group containing one tenth of the insured population. As the control variable, we used the number of the risk score decile group into which a person falls (and not the risk score itself), delayed by one year. The earliest year for which we were able to calculate risk scores deciles was 2013, and therefore 2014 is the first year in which they were used as control. Thus, to determine the effect of the intervention on hospital costs, we looked at the years 2014 to 2017, while the main estimation looked at the years 2012 to 2017.

2.3 Method

The difference-in-differences approach was used to determine the effect of the intervention. This relied on two assumptions: the Common Shocks assumption and the Parallel Trends assumption (Angrist and Pischke (2009)).

We fitted a Bayesian generalized multivariate multilevel model using Stan. Bayesian estimation gives a distribution of credibility over a range of estimates for a parameter, not just a point estimate with a confidence interval around it. The uncertainty around the estimate is captured by the distribution. After estimation, we were able to predict the intervention effect. We used no specific priors, but assumed a zero inflated Poisson distribution for the number of referrals and a zero inflated negative binomial distribution for spending on both hospital and GP care.

In the main estimation, we looked at hospital referrals. The intervention started in 2015 and has continued since then. In 2016, the GP practice in the intervention group switched from a fee-for-service system to a remuneration system in which they received an amount per registered person, causing incentives to change. A possible learning effect over time and/or these changed incentives may have caused the intervention to take on different effect sizes over the years. This is why we measured an intervention effect for each year separately.

Our main estimation equation was:

$$R_{igy} \sim \beta_0 + \beta_1 DiD2015 + \beta_2 DiD2016 + \beta_3 DiD2017 + \gamma Year + (1|Practice)$$

in which R refers to referrals of patient i assigned to GP-practice g in year y.

The DiD variables are binary variables that take the value 1 if the patient belongs to the intervention practice in a year after the treatment, and 0 otherwise. The year variables are year-fixed effects. We included a (1|Practice) variable in our Bayesian multilevel model to capture practice fixed effects, with a fixed intercept for each practice.

A placebo test was carried out in order to see whether the parallel trend assumption held. Parallel trends allowed us to hypothesize what the counter factual outcome of the treatment group would have been. This implied that absent the intervention, the number of referrals in the intervention group would have followed a trend similar to that of the control group.

We also looked at whether the intervention had an effect on hospital and GP spending. A decrease in referrals may have been visible in lower spending on hospital and GP care. These spending models contained year dummies, fixed effects for each GP practice, yearly intervention dummies for each year as of 2015 and a proxy for the case-mix of the registered person. The spending models differed from the hospital referral model, as they only included data from 2014 to 2017. This was because the risk equalization data required to create the risk scores was only available from 2014 onwards.

$$S_{igp} \sim 1 + \beta_1 DiD2015 + \beta_2 DiD2016 + \beta_3 DiD2017 + \gamma YEAR + \delta rs_{iy} + (1|Practice)$$

S refers to spending (either on hospital care, GP care or the total spending). We added the variable rs to indicate the risk score decile group for patient i in year y.

3 Results

3.1 Summary statistics

The table below presents summary statistics for the year 2014. We chose this year because it was the year immediately prior to the intervention, and because it was the first year for which we had access to the control variable "risk score".

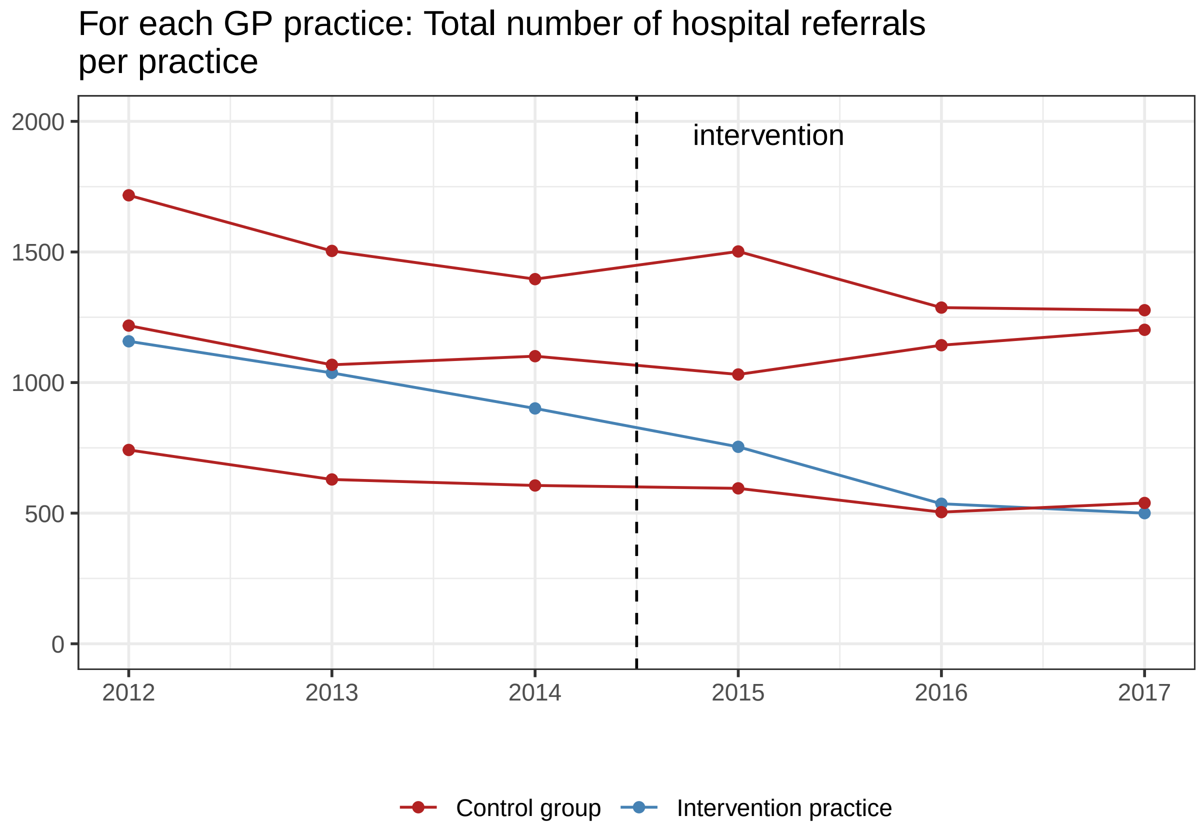
In the first quarter of 2014, a total of 2,681 individuals were registered with the intervention practice. Of these, 675 patients (900 referrals) were referred to the hospital. The table relates to the year prior to the intervention and illustrates the baseline characteristics of both the intervention group and the control group.

Table 1: Summary statistics

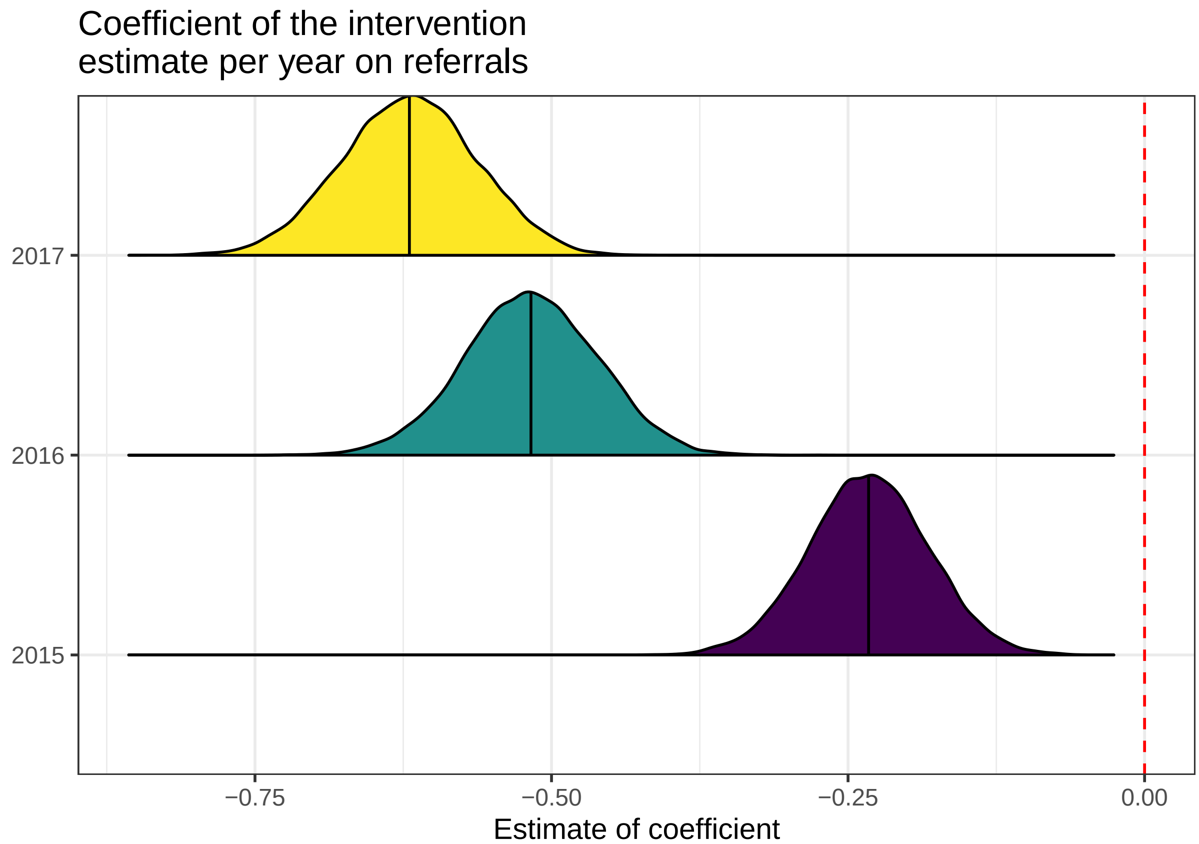
variable	Intervention group	Control group
Number of persons subscribed	2681	9539
Mean age	42.4	44.3
Share of subscribed persons referred	25	25
Male percentage	49.9	51.7
Total referrals	901	3103
Total patients referred	675	2338
standard deviation riskscore	1.89	1.86
Mean GP spending	188	157
Mean healthcare spending	1472	1390
Mean riskscore	1.09	1.12
standard deviation age	22.8	23
Interquartilerange of risk score	0.89	0.97

3.2 Referrals

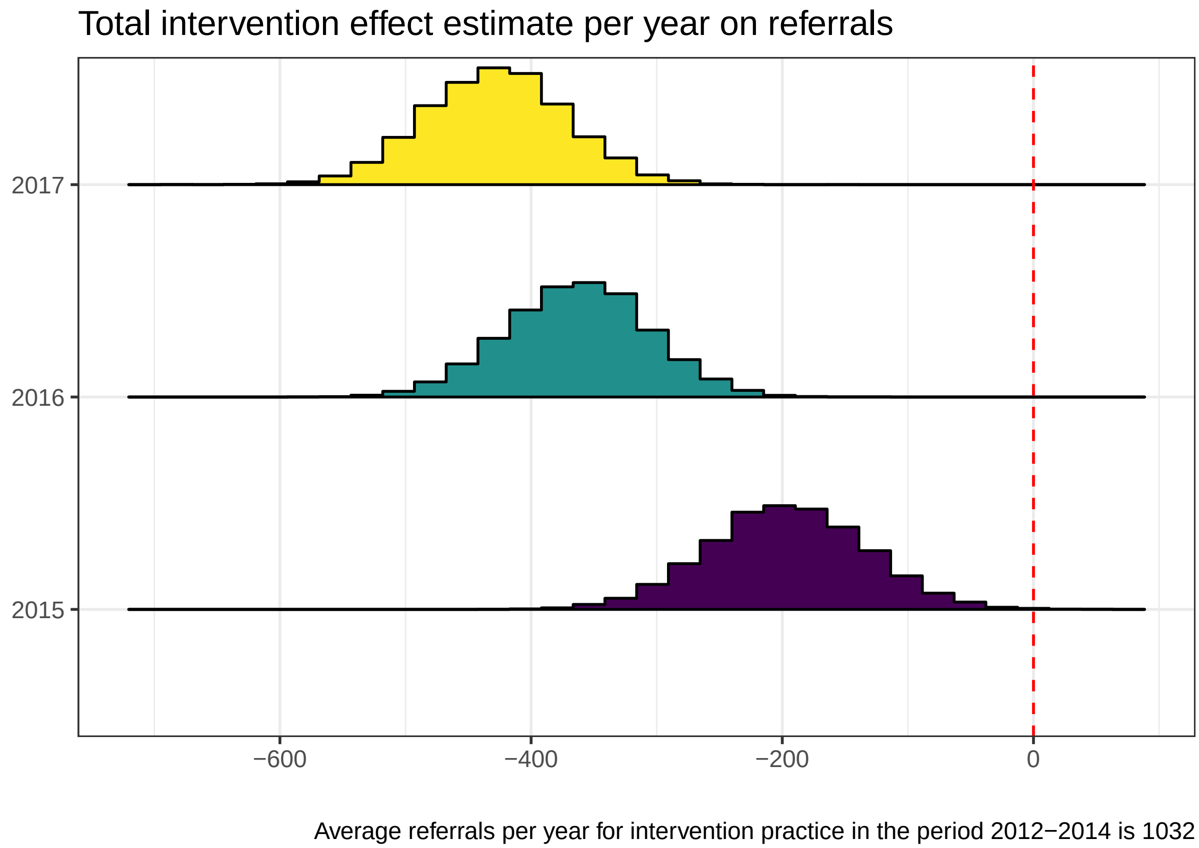
The graph below shows the number of referrals for both the intervention and control practices over time. The number of referrals made by the intervention practice was similar to the average for the control practices. Following the intervention, however, the number of referrals made by the intervention practice decreased compared to the control practices.



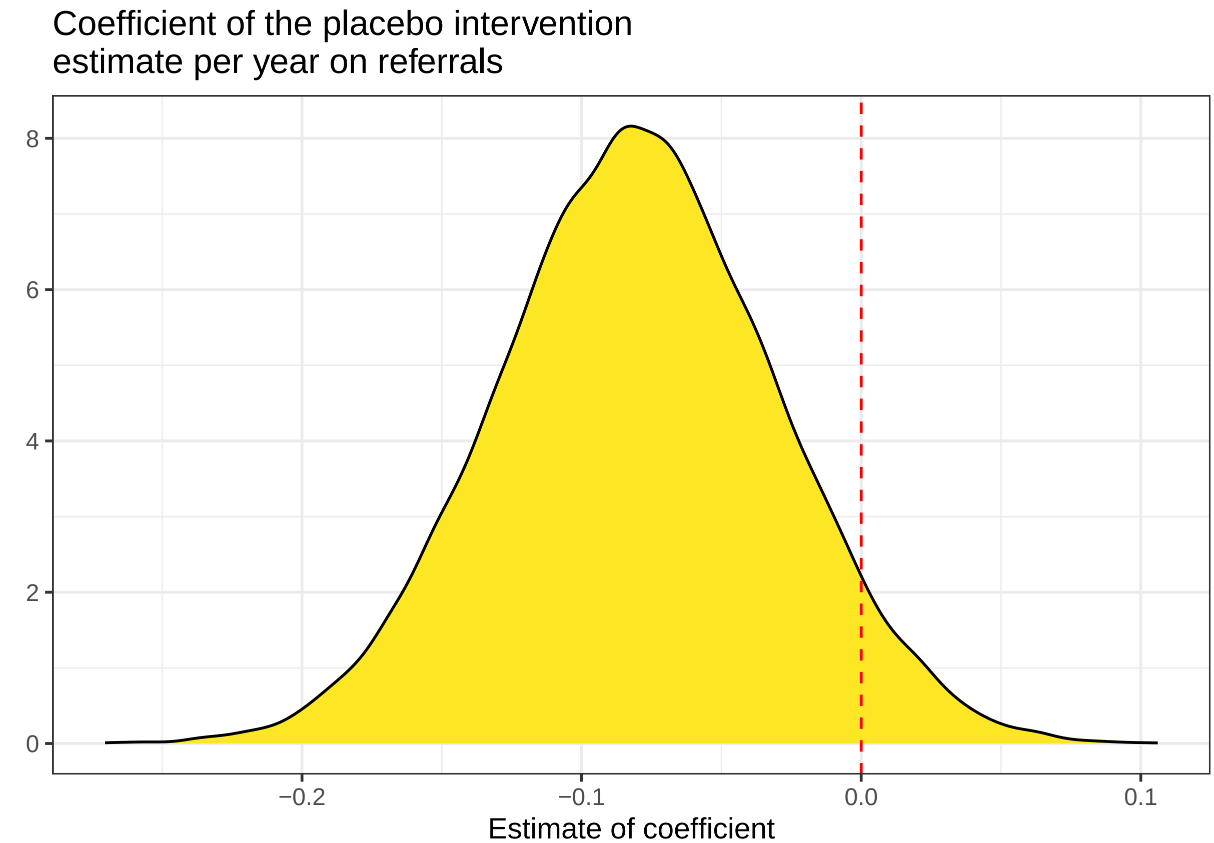
The results of our estimation show a reduction in the number of referrals after the intervention. The difference-in-difference coefficients are negative for each year, and zero is not included in the credible interval. The effect of the intervention increased over time and the intervals become more negative, which may be caused by a learning effect or by the reinforcement of the effect by the change to the payment system.



We used model predictions to evaluate the magnitude of the effect of the intervention. The figure below shows a probability distribution over the total reduction in referrals each year. The total reduction in referrals increases each year. In 2015, the intervention accounted for an average of 200 fewer referrals; in 2016, 350 fewer referrals; and in 2017 the number of referrals was reduced by an average of over 400.



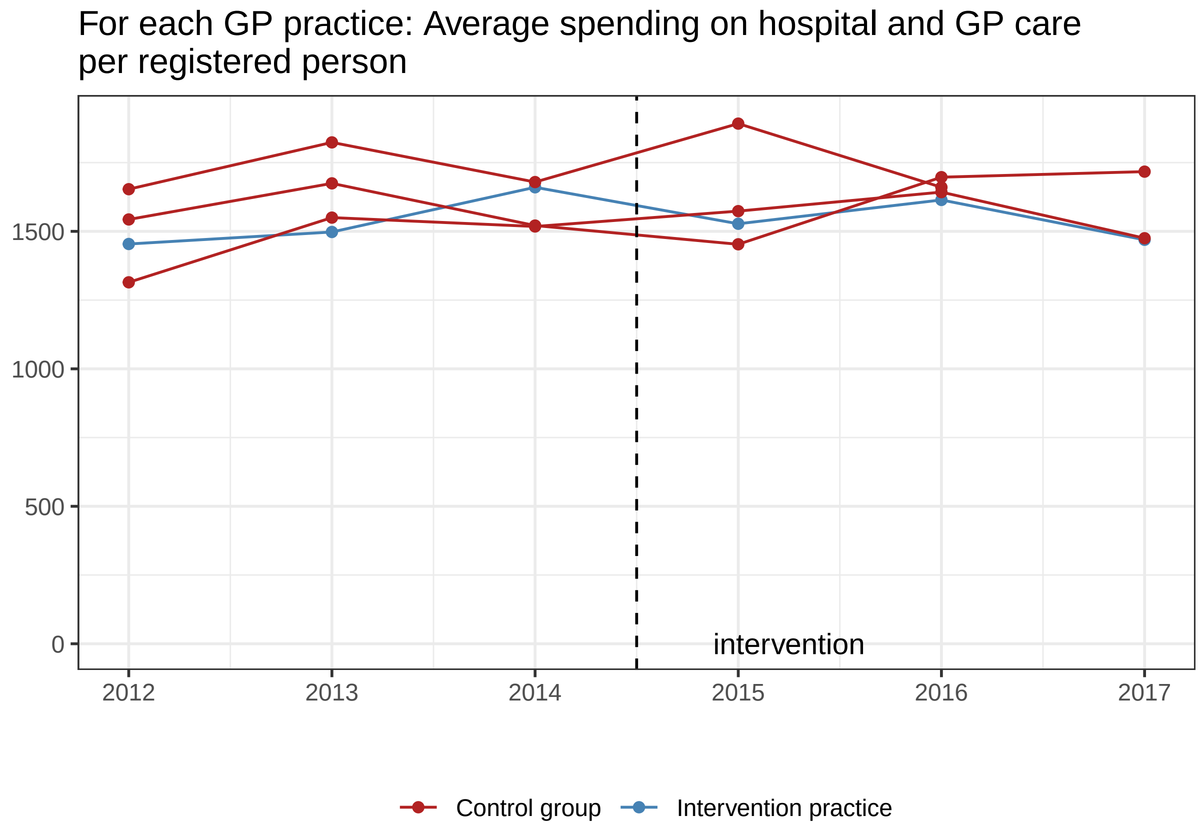
made by GP practices in both the intervention and control groups before the intervention. Zero is included in the credible interval, suggesting that a change in the number of referrals is not significantly associated with a placebo intervention in 2014. However, even though zero is included in the interval, there seems to be a probability that even before the intervention, referrals by the GP practice in Afferden were already on a downward trend compared to the control group. We believe that the GP Practice in Afferden was already experimenting with an alternative approach to treating patients, and based on the interviews at the GP practice, within the control group and with the insurer as well as the placebo test, we believe that the practices are comparable. We conclude that we will not reject the assumption of parallel trends.



3.3 Change in net spending

Our analysis shows a clear reduction in hospital referrals and we would expect a corresponding decrease in hospital spending, too. The intervention led to an increase in GP costs due to the increase in GP capacity. In this section, we present the results of the our analysis of the effect of the intervention on net spending (hospital spending plus GP spending). A separate analysis of the effects on hospital spending and GP spending is presented in the appendix.

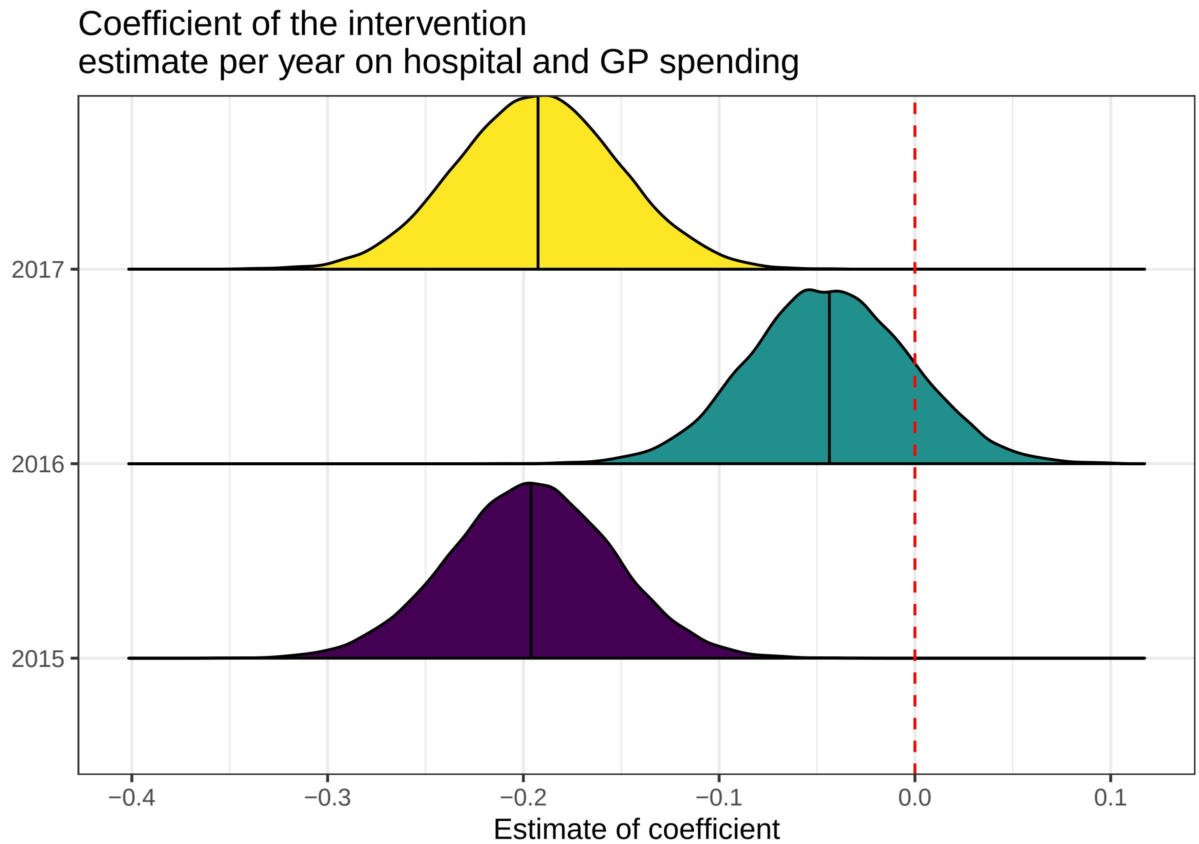
We see no effect of the intervention on the average unadjusted spending on hospital and GP care per individual. It is possible that the lack of any observed effect is due to the fact that spending on hospital care was not adjusted for patient-mix differences between the GP practices. We therefore adjusted for patient-mix differences in our analysis, as described in the methodology section.

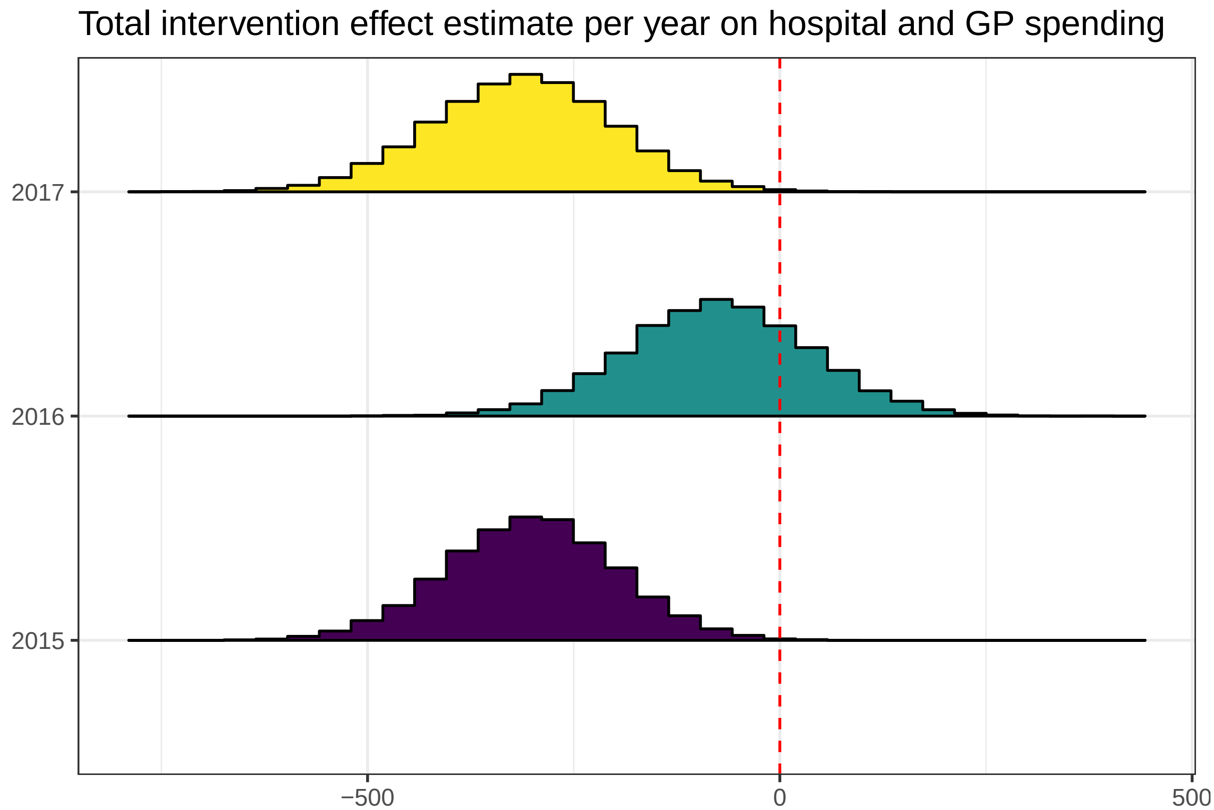


For this reason, we also computed the impact of the intervention on overall healthcare expenditure, defined as the combined cost of both GP and hospital spending.

The reduction in referrals is also visible in spending on hospital and GP care, although less clearly in the case of 2016. Since the cost of the intervention (which mainly took the form of increased GP spending) is relatively insignificant in comparison to the post-referral hospital costs incurred, the effect on total healthcare cost essentially aligns with the effect on hospital spending (see appendix).

For 2016, zero is included in the 95% credible interval of the DiD estimate, which means that there is a chance the intervention had no effect on hospital costs in particular. The results of the regression show that the intervention reduced hospital and GP spending in 2015 and 2017. The insurer VGZ and the GP practice in Afferden had no explanation for the different results in 2016. The results of our hospital spending model may be less robust than those of the referral model, because hospital spending data tends to include more variation and noise, and this could potentially have affected the accuracy of our estimates.


Coefficient of the intervention
estimate per year on hospital and GP spending
2017
2016
2015
−0.4
−0.3
−0.2
−0.1
0.0
0.1
Estimate of coefficient



4 Conclusion and Discussion

The intervention caused the number of referrals to the hospital to drop substantially, and the magnitude of this drop in referrals increased over time. Fewer referrals caused by the intervention also translated into lower spending on hospital care – at least in 2015 and 2017, and higher spending on total GP care. The net effect was a reduction in spending.

There are a few limitations of this intervention and this study.

The results of our study indicate that the intervention had an impact on healthcare usage. The number of referrals decreased and total healthcare costs also fell, even after taking into account the cost of extra GP capacity. However, several issues need to be taken into account with respect to the experiment and analysis. Firstly, we had no data on the primary outcome variable, which was health care outcomes. Based on discussions with the insurer and the GP practice, as well as a check of review websites, although we believe that there was no reduction in the quality of care, we cannot state this with absolute certainty. Secondly, it may be challenging to replicate this intervention in other practices. The Afferden practice was able to increase capacity by adding a GP for two days a week, but it would not be feasible for every GP practice to adopt this approach, given the shortage of GPs in the Netherlands. Finally, although the new funding structure removed the incentive to increase the number of visits, there was no incentivize to reduce the number of hospital referrals. Nonetheless, the intrinsic motivation of the GP practice to make the intervention successful and the knowledge that the insurer was monitoring the results likely played a significant role in the effect we observed in our analysis. In conclusion, our study demonstrates that the intervention had a positive impact, but further research is needed in order to fully understand whether the intervention affected health outcomes and its usefulness for other practices.

5 References

Andreyeva, Elena, Guy David, and Hummy Song. 2018. "The Effects of Home Health Visit Length on Hospital Readmission." National Bureau of Economic Research.

Angrist, Joshua D, and Jörn-Steffen Pischke. 2009. *Mostly Harmless Econometrics: An Empiricist's Companion.* Princeton university press.

Freedman, Seth, Ezra Golberstein, Tsan-Yao Huang, David Satin, and Laura Barrie Smith. 2021. "Docs with Their Eyes on the Clock? The Effect of Time Pressures on Primary Care Productivity." *Journal of Health Economics* 77.

Gaynor, Martin, James B Rebitzer, and Lowell J Taylor. 2004. "Physician Incentives in Health Maintenance Organizations." *Journal of Political Economy* 112 (4).

Hayen, Arthur, Michael Jack van den Berg, Jeroen Nathan Struijs, and Gerard Pieter Westert. 2021. "Dutch Shared Savings Program Targeted at Primary Care: Reduced Expenditures in Its First Year." *Health Policy* 125 (4): 489–94.

Huber, Machteld, Hans Peter Jung, Karolien van den Brekel-Dijkstra, Machteld Huber, Hans Peter Jung, and Karolien van den Brekel-Dijkstra. 2022. "Positive Health in Practice." *Handbook Positive Health in Primary Care: The Dutch Example*, 133–78.

Latimer, Nicholas R, Chris Henshall, Uwe Siebert, and Helen Bell. 2016. "Treatment Switching: Statistical and Decision-Making Challenges and Approaches." *International Journal of Technology Assessment in Health Care* 32 (3): 160–66.

Sripa, Poompong, Benedict Hayhoe, Priya Garg, Azeem Majeed, and Geva Greenfield. 2019. "Impact of GP Gatekeeping on Quality of Care, and Health Outcomes, Use, and Expenditure: A Systematic Review." *British Journal of General Practice* 69 (682): e294–303.

Ven, Wynand van de, Gerrit Hamstra, Richard van Kleef, Mieke Reuser, and Piet Stam. 2023. "The Goal of Risk Equalization in Regulated Competitive Health Insurance Markets." *The European Journal of Health Economics* 24 (1): 111–23.

Appendices

Estimates referral regression

Table 2: Results of the referral estimation

term	estimate	std.error	conf.low	conf.high
(Intercept)	-0.2762263	0.0950025	-0.4746653	-0.0824503
DiD20151	-0.2326729	0.0501842	-0.3320334	-0.1347640
DiD20161	-0.5173306	0.0558825	-0.6275440	-0.4084439
DiD20171	-0.6198064	0.0567465	-0.7312453	-0.5093669
JAAR2013	-0.1142378	0.0238861	-0.1615621	-0.0679151
JAAR2014	-0.2120671	0.0241663	-0.2596091	-0.1645464
JAAR2015	-0.1989975	0.0263216	-0.2509672	-0.1471617
JAAR2016	-0.2585190	0.0268250	-0.3118141	-0.2065086
JAAR2017	-0.2259140	0.0263510	-0.2773936	-0.1745855
sd___(Intercept)	0.1574953	0.1278671	0.0497269	0.5147755

Estimates placebo treatment referral regression

Placebo treatment tested for year 2014. DiD estimate has zero in the 95% credible interval.

Table 3: Results of the placebo referral estimation

term	estimate	std.error	conf.low	conf.high
(Intercept)	-0.2718107	0.1185864	-0.5285143	-0.0257801
DiD2014	-0.0803046	0.0497850	-0.1778940	0.0182414
JAAR2013	-0.1144975	0.0236355	-0.1607413	-0.0680721
JAAR2014	-0.1936822	0.0265078	-0.2464850	-0.1415970
sd___(Intercept)	0.2045436	0.1571112	0.0653540	0.6529986

Estimates hospital and GP costs regression

Table 4: Results of the hospital AND gp costs estimation

term	estimate	std.error	conf.low	conf.high
(Intercept)	6.1908582	0.0958026	5.9859393	6.3862720
DiD20151	-0.1960571	0.0413298	-0.2780184	-0.1153339
DiD20161	-0.0436916	0.0408702	-0.1232607	0.0361010
DiD20171	-0.1925024	0.0413007	-0.2730101	-0.1116988
decile2	-0.0637198	0.0287762	-0.1195630	-0.0073702
decile3	0.1036149	0.0289290	0.0465654	0.1609205
decile4	0.2560711	0.0287214	0.1997589	0.3129861
decile5	0.4108344	0.0285990	0.3543403	0.4662151
decile6	0.7493964	0.0278794	0.6946044	0.8034935
decile7	0.9398984	0.0280962	0.8843802	0.9950946
decile8	1.2116928	0.0275016	1.1572800	1.2654502
decile9	1.5991229	0.0270001	1.5458298	1.6511505
decile10	2.3844894	0.0268521	2.3317892	2.4374002
JAAR2015	0.0404896	0.0196711	0.0018387	0.0791800
JAAR2016	0.0790587	0.0196455	0.0406752	0.1178683
JAAR2017	0.1132377	0.0196290	0.0745461	0.1519770
sd___(Intercept)	0.1618293	0.1173925	0.0533484	0.5051757

Estimates hospital costs regression

estimates GP costs regression

Table 5: Results of the hospital costs estimation

term	estimate	std.error	conf.low	conf.high
(Intercept)	6.8212042	0.1242733	6.4851600	7.0572535
DiD20151	-0.2013396	0.0641829	-0.3269034	-0.0744035
DiD20161	-0.0915264	0.0660762	-0.2194978	0.0356488
DiD20171	-0.2832176	0.0662489	-0.4136697	-0.1548480
decile2	-0.0742522	0.0576441	-0.1885598	0.0378109
decile3	0.0732010	0.0565998	-0.0376479	0.1836669
decile4	0.1123909	0.0552185	0.0026948	0.2184342
decile5	0.2142564	0.0526427	0.1102580	0.3173050
decile6	0.5302057	0.0522313	0.4263727	0.6299352
decile7	0.6134877	0.0514882	0.5125716	0.7126273
decile8	0.7514824	0.0489037	0.6563360	0.8474075
decile9	1.0390956	0.0473361	0.9458752	1.1308025
decile10	1.7766256	0.0468654	1.6848900	1.8683005
JAAR2015	0.0318461	0.0311698	-0.0300670	0.0916243
JAAR2016	0.0563407	0.0317266	-0.0058343	0.1164101
JAAR2017	0.0931007	0.0310617	0.0315989	0.1540463
sd___(Intercept)	0.1997722	0.1899607	0.0566099	0.9370561

Table 6: Results of the GP costs estimation

term	estimate	std.error	conf.low	conf.high
(Intercept)	4.6673356	0.1119674	4.4330397	4.8876385
DiD20151	0.0041297	0.0171138	-0.0293799	0.0377466
DiD20161	0.1148367	0.0171863	0.0811743	0.1482985
DiD20171	0.1976760	0.0171480	0.1638387	0.2311270
decile2	0.0169446	0.0118078	-0.0062665	0.0399689
decile3	0.0546745	0.0118903	0.0311668	0.0779444
decile4	0.1207038	0.0117495	0.0978611	0.1435483
decile5	0.1515109	0.0115883	0.1291728	0.1745401
decile6	0.2046207	0.0115151	0.1819369	0.2269909
decile7	0.3035286	0.0115238	0.2810020	0.3261401
decile8	0.6083880	0.0112119	0.5860868	0.6300790
decile9	0.8715000	0.0110567	0.8498085	0.8933271
decile10	1.1480826	0.0109921	1.1262598	1.1696900
JAAR2015	0.1514883	0.0080575	0.1356348	0.1670631
JAAR2016	0.1924021	0.0081055	0.1765939	0.2082193
JAAR2017	0.2004502	0.0080582	0.1846439	0.2161750
sd___(Intercept)	0.1912827	0.1461037	0.0643467	0.5837048