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ABSTRACT

Health and Labor Market Consequences of Low-Value Care: The Role of Practice Style*

We investigate the health and labor market consequences of primary care variation in benzodiazepine prescriptions, a common type of low-value care. Linking Dutch general practitioners' records to administrative data, we construct an exogenous measure of prescribing behavior that exploits institutional constraints limiting patient choice. Using the loss of a close relative as a common mental health shock and a dynamic difference-in-differences approach, we find that patients treated by high-prescribing GPs are more likely to receive out-of-guidelines benzodiazepine prescriptions, become long-term users, and are less likely to access specialized mental health care. These patients also experience worse labor market outcomes, including increased short-term reliance on unemployment benefits and substantial long-term declines in earnings, primarily driven by reduced wages.

JEL Classification: I11, I18, J24

Keywords: benzodiazepine, primary care, prescribing style, mental health, labor market, bereavement

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1 Introduction

Mental health disorders are among the most pressing public health challenges of our time, constituting a leading cause of disability and mortality worldwide (James et al., 2018), interfering with human capital accumulation and labor market participation, and imposing significant productivity losses (OECD, 2012). Yet, many individuals do not receive the care they need (Thornicroft et al., 2017) and this influences their capacity to work, among other things. Treatment decisions, including referrals to specialized providers, are complex and often influenced by physicians' personal biases and practice styles rather than evidence-based guidelines (e.g., Currie et al., 2024; Cutler et al., 2019). This influences care quality and patient outcomes. A prominent example is the prescription of fast-acting medications like benzodiazepines (brand names include Valium, and Xanax), commonly prescribed for anxiety disorders and insomnia. These drugs provide short-term relief but carry significant long-term risks due to their addictive potential and other serious side effects (e.g., Soyka, 2017). For this reason, practice guidelines recommend behavioral interventions as first line of treatment, especially for insomnia (e.g., Edinger et al., 2021). Despite these concerns, benzodiazepines remain among the most frequently prescribed psychotropic medications in OECD countries, particularly in primary care settings. In the US, the estimated prevalence of use is over 12% among adults, increasing sharply with age (Maust et al., 2019).

In this paper, we investigate how the propensity to prescribe benzodiazepines of a general practitioner (GP) affects the patient's long-term health and economic well-being following a negative life event: the death of a close relative (i.e., a parent, spouse, child, or sibling). We use administrative data from the Netherlands merged with unique individual-level GP records on 2.6 million patients. To identify the causal effect of GP prescribing behavior, we exploit the Dutch health care system, where GPs act as gatekeepers and patients have limited choice (if any) of their provider (Currie and Zwiers, 2023). This institutional structure minimizes patient selection across practices, allowing us to treat GP assignment as exogenous once we include neighborhood fixed effects. We focus on individuals who had no benzodiazepine prescriptions or mental health diagnoses in the previous four years, thereby avoiding pre-treatment effects. We then use a dynamic difference-in-differences (DiD) model to estimate the impact of GPs' prescribing behavior on health and labor market outcomes following this plausibly exogenous mental health shock.

Enrollment in a GP practice at the 90th percentile of the estimated propensity to prescribe, relative to the 10th percentile increases the likelihood of receiving a benzodiazepine prescription by almost 30% following the death of a relative. This effect persists for at least 6 years, and it is driven by prescriptions that are flagged as potentially inappropriate under Dutch GP guidelines for treating mental health problems. Persistent use also increases: patients treated by high-prescribing GPs are more likely to receive six or more prescriptions per year for at least three consecutive years. Furthermore, a higher propensity to prescribe benzodiazepines reduces the likelihood of receiving specialized mental health care, which in our setting primarily consists of psychotherapy.

A higher propensity to prescribe benzodiazepines also has substantial labor market implications. Patients enrolled at a practice at the 90th versus the 10th percentile experience a decline in employment probability in the short term—with an increasing probability of receiving unemployment benefits—and see progressively lower earnings, reaching a 4% drop by the fifth year after the relative's death. This decrease in earnings is primarily due to lower wages and is most pronounced among males under 50, and arises only among patients enrolled in high-prescribing practices (highest tercile).

To understand the mechanisms driving these results, we first investigate if the estimated effects stem exclusively from differences in benzodiazepine prescription rates across GPs, or other practice-level factors correlated with benzodiazepine prescribing. We test for similar increases in the prescription of other mental health-related drugs. While the death of a close relative might trigger an increase in depressive symptoms, we do not observe a statistically significant increase in antidepressant prescriptions that is correlated with the propensity to prescribe benzodiazepines. Opioid prescriptions increase among patients treated by GPs with a higher propensity to prescribe benzodiazepines but this effect occurs only after 3-4 years, suggesting that the use of these drugs might be a consequence of long-term use of benzodiazepines. Second, we construct a propensity to prescribe antibiotics, another class of drugs often subject to overprescribing and commonly regarded as low-value care treatment (Müskens et al., 2022). While the propensity to prescribe antibiotics is positively correlated with that of benzodiazepines, we do not find meaningful differences in health and labor market outcomes across patients enrolled in GP practices with different propensities to prescribe antibiotics.

Finally, we investigate the role of mental health nurses employed in the GP practice to provide talk therapy, counseling, and basic cognitive-behavioral techniques for patients with mild psychological issues. Specifically, we exploit the staggered introduction of these nurses into Dutch GP practices after they were included in basic health insurance coverage starting in 2008. We show that their introduction in the GP practice substantially reduces the gap in benzodiazepine prescribing between high- and low-propensity practices, leading to a corresponding narrowing of labor market outcome differentials. This evidence indicates that basic non-pharmaceutical therapy within primary care may represent a suitable alternative to benzodiazepine treatment with positive spillovers for patients' long-term labor market outcomes. Moreover, it supports our conclusion that the adverse labor market consequences stem primarily from excessive benzodiazepine prescribing.

We further assess the robustness of our findings to potential violations of the identifying assumptions. First, we relax the requirement that, conditional on neighborhood fixed effects, patients are quasi-randomly assigned to GP practices. Specifically, we construct an alternative measure of prescribing propensity that only assumes patients cannot predict changes in a GP's prescribing behavior after a relative's death—allowing for possible self-selection based on the GP's overall prescribing style. In addition, we test for anticipatory effects by excluding cancer-related deaths and investigate heterogeneity by type of bereavement (e.g., loss of a parent, child, spouse, or sibling) and across terciles of benzodiazepine prescribing propensity. Finally, we rule out confounding influences from differential survival or inheritance.

Our study contributes to the growing body of research investigating the consequences of physicians' practice style variation in health care (e.g., Currie et al., 2024; Finkelstein et al., 2021). We focus on general practitioners who are often the starting point of any health care treatment and who are responsible for the majority of psychotropic drug prescriptions in the Netherlands (Noordam et al., 2015), as well as in many other OECD countries (e.g., Mojtabai and Olfson, 2011). Currie and Zwiers (2023) exploit geographical variation in antidepressant prescribing behavior, finding that postpartum antidepressant use increases long-term medication use and reduces short-term employment for lower-income women. Similar patterns have been documented in other countries. For example, Fadlon and Van Parys (2020) show how general practitioners' treatment decisions in the US strongly influence patients' health care utilization and spending, while Eichmeyer and Zhang (2023) quantify the long-term effects of GPs' opioid prescribing tendencies on opioid use and abuse using quasi-random assignment of providers to veterans. Our study is the first to isolate the causal impact of GPs' prescribing behavior on patients' long-term labor market outcomes. This uncovers an unexplored aspect of physician practice styles, extending their influence beyond immediate healthcare utilization to lasting impacts on employment and earnings.

There is also growing evidence on the labor market impact of mental health drug treatments (Biasi et al., 2021; Butikofer et al., 2020; Masiero et al., 2020; Shapiro, 2022). Yet, these studies do not focus on how physician prescribing styles shape treatment decisions, nor they address benzodiazepines specifically, which remain one of the most commonly prescribed classes of psychotropic drugs and a major public health concern.

Our findings align with recent research showing that physicians often deviate from clinical guidelines (e.g., Cuddy and Currie, 2020; Finkelstein et al., 2022) leading to poorer patient outcomes (Abaluck et al., 2020; Currie and MacLeod, 2020). Indeed, we show that Dutch GPs often deviate from clinical guidelines regarding benzodiazepine prescriptions and that a higher propensity to prescribe is associated with more frequent deviations from these guidelines.

Our work also relates to the literature on the impact of the loss of a close relative on health and labor market outcomes (van den Berg et al., 2017; Fadlon and Nielsen, 2019; 2021), effects that can even persist across generations (Black et al., 2016; Persson and Rossin-Slater, 2018). We add to these studies by showing significant heterogeneity in the negative effects of grief that are caused by variations in physician practice styles and resulting treatment choices. In particular, we find that only patients of high-prescribing practices suffer the negative and persistent labor market consequences of bereavement.

We further add to the literature on the health effects of benzodiazepine use. Böckerman et al. (2024) find that increased availability of these drugs, facilitated by e-prescribing software, reduces hospitalizations in the short run but raises the incidence of prescription drug poisonings among those under 65. In contrast, it lowers prescription drug abuse among the 65+ population.[1]

[1]Medical research primarily examines these effects in controlled settings focusing on short-term outcomes (e.g., de Gage et al.,

Our paper offers new insights into ongoing discussion on the optimal allocation of resources in mental health care (e.g., Olfson, 2016). In many countries, there has been a shift away from specialized mental health care, such as psychotherapy, due to supply constraints and cost considerations, leading to increased reliance on prescription drugs like benzodiazepines in primary care. Whether this shift is appropriate for the marginal patient—i.e. whether gatekeeper GPs get this balance right at the margin—remains an empirical question. Recent research indicates a declining share of patients receiving therapy and counseling, the recommended treatment for most mental health conditions (Holmes et al., 2018). At the same time, expanding access to psychotherapy can reduce reliance on other mental health services and improve mental health outcomes (Serena, 2021). Our findings show that high-prescribing GPs drive a shift toward benzodiazepine-based treatment, which leads to adverse labor market outcomes. This is consistent with Prudon (2023), who documents detrimental effects on employment of delayed access to mental health specialists due to waiting times.[2] In this context, we find that the introduction of mental health nurses in primary care—trained to offer talking therapy and counseling without having prescriptive authority—significantly narrows the gap in benzodiazepine prescribing rates between high- and low-prescribing GPs, thereby reducing disparities in labor market outcomes. This evidence suggests that ensuring adequate access to non-pharmacological mental health support in primary care can effectively counterbalance excessive prescribing and mitigate its negative economic impacts.

As the first point of contact and gatekeeper to specialized mental health services, GPs play a decisive role in shaping patients' health trajectories and labor market prospects. Our study underscores the need for policy interventions aimed at enhancing guideline adherence and expanding non-pharmacological treatment options in primary care.

2 Background

The Dutch Healthcare System

The Dutch mandatory health insurance system provides universal, comprehensive coverage with very limited opportunities to bypass the public system: only 2% of total expenditures on mental health care was private spending in 2015, while private spending on general practitioners (GP) was 1% of the total spending on this type of care (CBS, 2017).

GPs act as gatekeepers for specialist care including mental health care provided by psychologists or psychiatrists; specialized medical treatment is only reimbursed through public health insurance when the patient is referred by a GP or admitted through the emergency department. GP treatment is exempt from the deductible and hence free from the point of view of the patient; medical testing and medication prescribed by GPs are not exempt. In 2019, there were 12,766 general practitioners (GPs) working across 5,677 GP practices in the

2014) or relies on observational studies (e.g., Bachhuber et al., 2016), which are not designed to establish the causal impact of benzodiazepine (mis)use.

[2]Our results are not driven by regional differences in waiting times, which we show are not correlated with GP's propensity to prescribe benzodiazepines 5.5.

Table 1: Geographical distribution of GP's patients relative to practice location

	Geographical Unit	
	Neighborhood	Block
Mean distance from GP practice (Km)	3.05	3.59
Patients living in the same neighborhood/block as their GP practice	58.60%	29.17%
Patients living more than 10 Km from GP practice	3.8%	3.9%

Note: The table shows the geographical distribution of patients' residences relative to the centroid of their GP's practice neighborhood or block. The GP practice location is approximated using the mode of all its patients' geographical units. Neighborhood ("wijk") and block ("buurt") refer to the definitions by Statistics Netherlands.

Netherlands, with an average of 2.4 GPs per practice. Only 17.5% of these practices were run by a single GP. Each practice typically employs additional support staff for tasks such as triage (practice assistants) and routine follow-up for chronic conditions (including mental health nurses[3]), which allows GPs to delegate certain responsibilities. On average, a GP practice serves 2,095 registered patients, employs 1.23 full-time equivalent staff, and handles 8,966 patient visits annually. GP practices operate five days a week during regular business hours, while out-of-hours care is centralized across 53 regions with 105 clinics. GP care accounts for 4% of total healthcare spending in the Netherlands (Batenburg et al., 2022).

Virtually all Dutch residents register with a GP practice of their choice, but this choice is constrained by two key factors: *i)* GPs typically accept only patients residing within a 15-minute commuting distance from the practice, ensuring they can make emergency house calls (Kroneman et al., 2016), and *ii)* the GP must have available capacity to accept new patients. Although patients technically have free choice of practice, these restrictions significantly limit their options and prevent practice shopping, i.e., selecting practices for easier referrals or prescriptions. Patients are only able to visit the GP practice with which they are registered, except when, for example, on holiday elsewhere in the country.

Table 1 provides an overview of the geographical distribution of patients in relation to their GP practice location. Regardless of the geographical unit used to measure the distance—whether neighborhoods (Wijken) or blocks (Buurten)—the GP's catchment area is very restrictive. Nearly 60% of patients reside in the same neighborhood as their GP practice, and only 2% live more than 10 km away. This pattern is similar at the finer geographical level: almost 30% of patients live in the same block as their GP, while only 4% are more than 10 km away. To illustrate the level of granularity provided by this geographical breakdown, Figure A.1 presents a map showing the division of Amsterdam into its neighborhoods. There are 99 neighborhoods only in the city of Amsterdam and over 3,000 across the country.

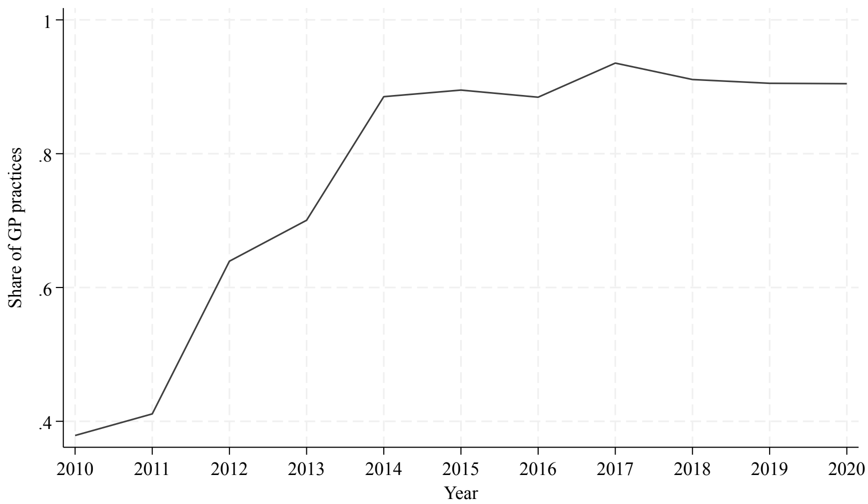
[3]Mental health nurse visits have been covered by public health insurance since 2008 (NZa, 2013).

The starting point of mental health treatment in the Netherlands is the GP.[4] Patients with mental health symptoms are diagnosed and treated by their own GP. The treatment might include medication (e.g., benzodiazepines and/or antidepressants) to manage symptoms. Follow-up visits may be delegated to the mental health nurse—if present in the practice—for continued care.

Mental health nurses, covered by basic health insurance since 2008 (NZa, 2013), support GPs by offering talking therapy, counseling and basic cognitive-behavioral techniques for patients with mild psychological issues such as stress, burnout, anxiety, and mild depression. For this, they receive specific training. Mental health nurses cannot prescribe drugs. Figure 1 shows the rapid increase in the share of practices in our sample that employed mental health nurses beginning in 2011. Although 40% of practices already included them in their staff by 2010–2011, this share rose sharply within three years (2012–2014) to over 80%.

If the GP suspects a more severe mental health disorder, based on the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) criteria, they may refer the patient to a specialized mental health care provider. Once referred, specialized mental health care is covered by the public health insurance scheme. During the study period, there was typically a waiting time for access to specialized mental health services of 62 days from first contact to treatment start (Prudon, 2023).

Figure 1: Share of GP practices with mental health nurse



Notes: The figure shows the share of GP practices with any mental health nurse between 2010 and 2020. Number of GP practices= 534. Number of observations (practice X year)= 3,908. Source: Nivel and Statistics Netherlands microdata.

[4] This paragraph describes the situation since the 2014 reform, which is relevant for most of the study period. Before 2014, mental health care was split into primary mental health care (28% of patients), and secondary mental health care. The former did not strictly require a referral, while the latter required a referral from a GP or a primary mental health care provider (Lambregts and van Vliet, 2018).

Benzodiazepines and Guidelines

Benzodiazepines[5] are commonly prescribed drugs used to manage symptoms of insomnia, anxiety, and, less frequently, for other psychotic disorders and chronic pain. Most of these conditions are linked to underlying mental health problems. For instance, insomnia can be triggered by acute stress (Morin and Benca, 2012). Benzodiazepines are known to be effective in the short-term management of insomnia and anxiety and relatively inexpensive (one euro for a daily dose, Healthcare Institute Netherlands, 2022), but they have a high addictive potential and evidence of their long-term efficacy is scarce (Baldwin et al., 2013). In addition, side effects may be harmful, especially among the elderly, and increasing evidence of higher long-term efficacy of cognitive behavioral therapy (CBT) to treat anxiety and insomnia (Baranov et al., 2020; Morin and Benca, 2012). Thus, physicians face a decision for every patient to weigh positive short-term effects against the risk of long-term negative side effects (Böckerman et al., 2024).

The global Choosing Wisely initiative has included their use, especially among the elderly, in the top list of low-value care treatments (Fund, 2017). Most developed countries have also detailed national guidelines for the safe use of benzodiazepines.

In the Netherlands, 8.5% of the population used benzodiazepines in 2019 (CBS, 2020; SFK, 2020), a figure that was even higher a decade earlier (10.7% in 2007; GIP-databank, 2024). In 2009, the Dutch government passed a reform limiting health insurance reimbursement of benzodiazepines to very specific and relatively uncommon diagnoses.[6] The reform led to an estimated reduction in the prevalence of benzodiazepine use by almost 18% and to a lower extent of the prevalence of long-term users (Stoker et al., 2019).

Table 2 presents descriptive statistics on benzodiazepine prescriptions at the GP practice level, including the share of potentially inappropriate prescriptions based on the Dutch guidelines for GPs that we were able to identify in the data.[7] We refer to these as "red flag" (RF) treatments, a term already used by Cuddy and Currie (2020) relative to antidepressant prescriptions for children in the US.

The average annual prescription rate in our data is 8.2%, which aligns closely with the national average reported above. More importantly, roughly 40% of these prescriptions are marked as potentially inappropriate. Specifically, we identify four types of treatments that can be flagged in our dataset: *i)* the first prescription of a benzodiazepine without a justifying diagnosis; *ii)* the first prescription with only a diagnosis of feeling anxious/nervous/tense [8]; *iii)* prescriptions that extend beyond 3 months; *iv)* concurrent prescriptions of benzodiazepines and opioids within the same month.

[5]In what follows, the term benzodiazepine is meant to include z-drugs which act similarly and result in comparable addiction and long-term problems.

[6]Benzodiazepines are still reimbursed to individuals with epileptic seizures, anxiety disorders in which at least two anti-depressants fail to ameliorate symptoms, multiple psychiatric conditions that necessitate the administration of high doses of benzodiazepines, and muscular spasms resulting from neurological disorders. Also, palliative sedation used in terminal care is exempted from this regulation.

[7]See guidelines for anxiety (NHG, 2019), depression (Claassen et al., 2024), and sleep problems (Bhogal-Statham et al., 2024).

[8]International Classification of Primary Care (ICPC) code P01

Table 2: Benzodiazepine prescriptions at practice level and share of potentially inappropriate prescriptions, Red Flags (RF)

	Mean	SD	25th	75th
Share of patients with a benzodiazepine prescription	0.082	0.019	0.069	0.095
RF 1: 1st prescription and no justifying diagnosis	0.117	0.073	0.085	0.147
RF 2: 1st prescription and diagnosis: feeling anxious/nervous/tense	0.039	0.026	0.023	0.052
RF 3: prolonged prescriptions (more than 3 months)	0.202	0.062	0.160	0.238
RF 4: benzodiazepine and opioids in the same month	0.129	0.031	0.110	0.148
Any RF prescription	0.409	0.083	0.361	0.46
Probability of 6 prescriptions in 3 years	0.008	0.007	0.00	0.013

Notes: Number of GP practices= 534. Number of observations (practice X year)= 3,908. Red-flag prescriptions are always in relation to the total number of patients with benzodiazepine prescriptions in a year. Diagnosis of feeling anxious/nervous/tense refers to International Classification of Primary Care (ICPC) code P01. Source: Nivel and Statistics Netherlands microdata.

While some of these flagged prescriptions may be appropriate in certain cases, inappropriate prescriptions are likely under-identified in the data because we can focus only on clearly inappropriate situations. Among the red flag treatments, the most common is prolonged prescriptions, which account for approximately 20% of benzodiazepine prescriptions. This is followed by the concurrent use of benzodiazepines and opioids, comprising nearly 13% of cases. Although prescribing without a justifying diagnosis (RF1) or with only a diagnosis for feeling anxious/nervous/tense (RF2) also occur, prolonged use (RF3) and concurrent benzodiazepine-opioid prescriptions (RF4) are the two categories where there is the least uncertainty about their appropriateness.

In addition to these flagged prescriptions, we focus on long-term (or chronic) use, defined as the number of individuals receiving at least six prescriptions per year for three consecutive years (last row of Table 2). These individuals may be at higher risk of developing dependence or addiction

3 Data and Sample Selection

Datasets We use Dutch administrative microdata provided by Statistics Netherlands (Centraal Bureau voor de Statistiek, *CBS*). The data include GP records from the Netherlands Institute for Health Services Research (Nivel, 2021) for the years 2009-2020,[9] health insurance claims from *Vektis*, outpatient medication use from

[9]This study has been approved according to the governance code of Nivel Primary Care Database, under number NZR-00312.021. The use of electronic health records for research purposes is allowed under certain conditions. When these conditions are fulfilled,

the Health Care Institute, demographic information from the mandatory Municipal Registry and Statistics Netherlands, income tax records from the Tax Office, and employment records from the Social Security Administration. The GP records are available for about 10% of all GP practices, which have about 2.6 million patients, which is roughly 15% of the overall Dutch population.

The GP records contain patient-level information about all their diagnoses and prescriptions related to mental health issues and a GP practice identifier.[10] In the Appendix, we show that the population of this subsample of GP practices is representative of the whole Dutch population (Table A.1).

Outcomes and Background Characteristics We use three sets of outcome variables, starting with benzodiazepine prescriptions. We examine both prevalence—whether an individual has a benzodiazepine prescription in a given year—and long-term use, defined as receiving at least six prescriptions annually for three consecutive years. Because most benzodiazepine prescriptions are not covered through public health insurance, they do not appear in the administrative records on medication use that are available for the full population. Instead, we use the GP records. This means that we capture benzodiazepine prescriptions by the GP, but not those prescribed by psychiatrists or other medical specialists. Yet, 80% of all benzodiazepine prescriptions filled by outpatient pharmacies come from GPs; 13% by medical specialists including psychiatrists, and 7% by doctors working in institutional settings (SFK, 2022). Figure A.2 compares the share of patients with at least one benzodiazepine prescription between 2006 and 2020 in the administrative records on medication based on insurance reimbursement and in the GP prescription data from Nivel.

Second, we take information on healthcare spending from the health insurance claims data. The health insurance claims pertain to basic public health insurance, which provides comprehensive medical care coverage and is mandatory. From these data, we use information on annual expenditures for GP visits, medication, hospital care (both inpatient and outpatient care), and mental health care (psychiatrists and psychotherapists).

Third, we analyze three labor market outcomes: total (after-tax) individual income from work, unemployment insurance benefits as the main source of income, and, for employees only, the base wage rate stipulated in employment contracts, excluding overtime.

The three sets of outcome variables are complemented with demographic information including information on the date of birth, date of death (and its reason), and gender, which also facilitate the identification of partners, children, and siblings. We also collect information on contacts with the GP's mental health nurse (praktijkondersteuner GGZ) to whom follow-up visits may be delegated, to identify whether a mental health

neither obtaining informed consent from patients nor approval by a medical ethics committee is obligatory for this type of observational studies containing no directly identifiable data (art. 24 GDPR Implementation Act jo art. 9.2 sub j GDPR).

[10] Prescriptions are coded following the Anatomical Therapeutic Chemical (ATC) classification system groups N03AE, N05A, N05B, N05C, or N06A. Diagnoses are coded following the International Classification of Primary Care (ICPC) 2 P01-P10, P15, P17-P20, P25, P27, P71-P80, A01, L01-L03, L86, N94 and the Z-chapter. For more information on ATC codes visit https://www.whocc.no/atc_ddd_index/, and for more information on ICPC codes visit https://info.famenet.nl/about/icpc/icpc-list/. Moreover, for those patients with at least one prescription for a mental health problem or at least one mental health diagnosis, we observe all the other prescriptions and diagnoses.

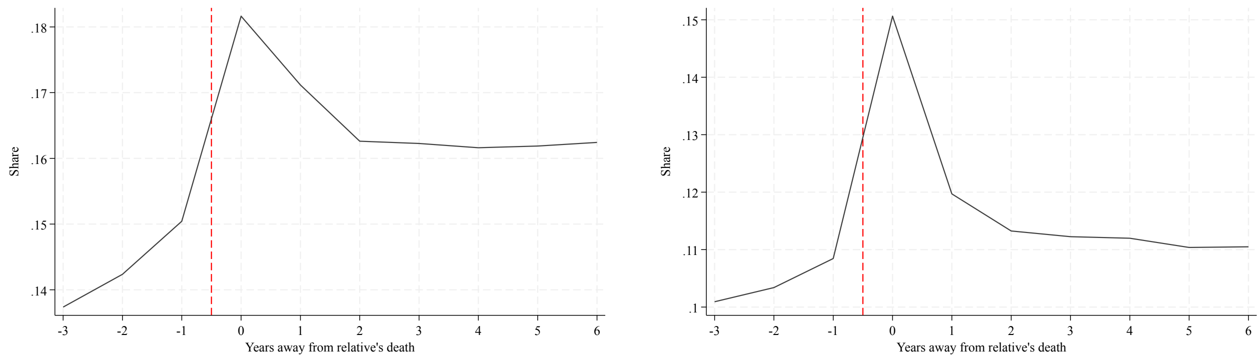
nurse was present in the practice at the time of bereavement.

Sample selection In this study, we use two samples. The first sample includes all individuals observed in GP medical records between 2009 and 2020. This sample is used to estimate the GP practice propensity to prescribe benzodiazepines (see Section 4.1).

The second sample is used to estimate the effects on healthcare use and labor market outcomes of being treated by GP practices with different propensity to prescribe benzodiazepine after the death of a close relative. For this analysis, we first restrict the sample to all individuals who were aged 18–60 at the time they experienced the loss of a child, spouse, parent, or sibling between 2010 and 2016. While we have information on people experiencing a loss in other years, we impose this restriction to ensure that we can observe all individuals for at least one year before and four years after the shock. Second, we restrict the sample to individuals who are observed in the GP records in the year of the loss and the prior year.

The loss of a relative triggers mental health diagnoses and benzodiazepine use (Figure 2). While on an increasing trend, diagnoses of mental health issues sharply increased at the time of the loss (event time 0) by almost 30% (left panel). Social problems,[11] insomnia, mild anxiety, and burnout diagnoses increase the most after the loss of a relative (Appendix Figure A.3). Furthermore, benzodiazepine take-up rates increase sharply by over a third (roughly 4 percentage points) at the time of the loss but subsequently slowly return slightly above the levels observed in the years before the loss (right panel).

Figure 2: Mental Health Diagnoses and Benzodiazepine Prescription and Relative's Death



(a) Mental health diagnoses (b) Benzodiazepine prescriptions

Notes: The figure shows the share of patients with any psychological or social issue diagnosis before and after the loss of a relative (left). The loss occurs between 2009 and 2016. N=288,587. Source: Nivel and Statistics Netherlands microdata.

A potential identification issue that arises from Figure 2 is that many patients were already diagnosed and treated for mental health issues before the event. Treatment before the event may have long-term consequences, which may be different across patients treated by GPs with different practice styles. Hence, we further restrict

[11] Social problems refer to any mental problem that relates to various aspects of life (work, relationships, and many others).

our sample to patients who did not have any psychological diagnosis or benzodiazepine prescription before the shock. This leads to a final sample of 76,407 patients. This restriction is relaxed in a robustness check (section 5.5) to show that our results can be generalized to the entire study sample. Appendix Table A.2 summarizes the sample selection criteria and the resulting sample sizes. The final study sample is, on average, older and shows a lower share of immigrants than the overall population (Appendix Table A.3).

4 Research Design

We explore the impact of a GP's propensity to prescribe benzodiazepines on patients' long-term health and labor market outcomes following a mental health shock: the loss of a close relative. To estimate these effects, we employ a dynamic staggered difference-in-differences (DiD) model tracking patients over an 11-year window: from four years before to six years after the event. By comparing patients who experienced similar shocks but were treated by GPs with different prescribing styles, we aim to understand how these differences affect patient outcomes over time.

A crucial part of our design involves constructing each GP practice's propensity to prescribe benzodiazepines. We exploit the limited patient choice in the Dutch healthcare system, where patients are typically registered with GP practices based on proximity and capacity, to mitigate concerns about self-selection into specific practices. We calculate a residualized leave-one-out prescription rate that accounts for patient differences correlated with geographical factors and temporal effects.

The remainder of this section is organized as follows. First, we detail the construction of the GP's propensity to prescribe benzodiazepines. Next, we describe the dynamic DiD model and its implementation. Finally, we discuss the identifying assumptions underlying our approach.

4.1 Propensity to prescribe benzodiazepines

We measure practice propensity to prescribe benzodiazepines as the time-invariant residualized leave-one-out average benzodiazepine prescription rate. Following the judge fixed effect literature (e.g., Aizer and Doyle Jr, 2015), we calculate it in two steps. First, we obtain the residuals from the following regression equation, estimated including all patients registered with the Nivel GP practices over the observation window (2009-2020):

$$Prescribed_{ijt} = \gamma_0 + \gamma_t + \gamma_w + \theta X_{it} + \varepsilon_{ijt} \tag{1}$$

where $Prescribed_{ijt}$ is a dummy that equals one if patient i was prescribed a benzodiazepine by practice j, at time t. GP choice is very limited in the Dutch health care system, so differences in prescribing rates should mainly arise as the result of differences in prescribing style. Yet, we include a set of fixed effects to control for the residual differences in patients' characteristics that are driven by time, γ_t, and neighborhood γ_w

differences.[12] In particular, we include neighborhood fixed effects to account for differences in the patient pool across practices that arise, e.g. because of neighborhood-level health differences. We also include a vector of basic socio-demographic controls X_{jt} (age bins, migration background, and sex) to increase precision.[13]

We then construct a propensity to prescribe benzodiazepines for each individual i as the average residual over all other patients in the sample seen by the patient i's practice, excluding patient i from the average:

$$pp_i^j = \frac{1}{N_{-i}^j} \sum_{i' \neq i} \sum_t \hat{\varepsilon}_{ijt} \tag{2}$$

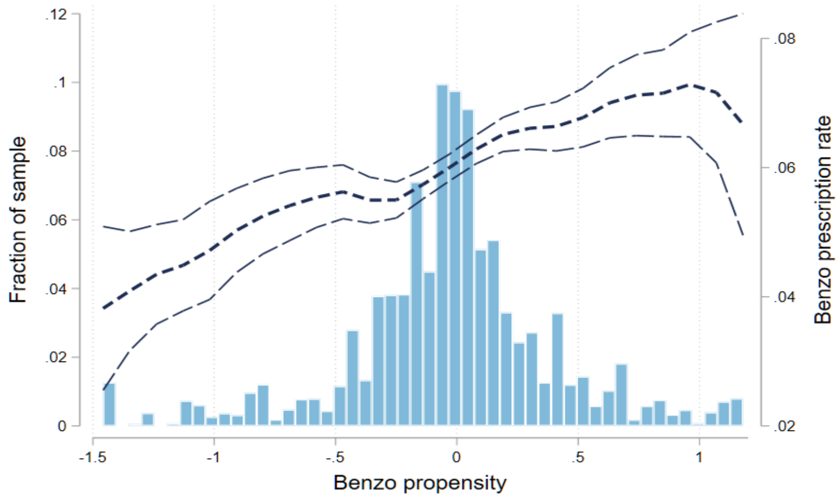
Since the fitted values of the residuals from Equation (1), $\hat{\varepsilon}_{ijt}$, have limited variation over time [14], we average these residuals across years, to construct our time-invariant measure of the practice's propensity to prescribe. We normalize the time-averaged residuals by the difference between the 10^{th} and 90^{th} percentiles of the residualized distribution (as in Eichmeyer and Zhang, 2021). Consequently, a one-unit shift in our metric corresponds to moving from a general practitioner in the lowest decile (a low-prescribing GP) to one in the highest decile (a high-prescribing GP). Because some patients may switch GPs over time and we are interested in the effect of the GP at the time of the initial treatment, we assign each patient to the GP they had at the time of loss. This results in a unique GP propensity per patient. In an alternative specification, we categorize the sample based on the terciles of the practice's propensity-to-prescribe distribution.

[12] We check whether we have sufficient variation left once including neighborhood fixed effects. Specifically, there are no GP practices with all their patients from the same neighborhood, and only 27 GP practices have at least 90% of their patients in their same neighborhood.

[13] The estimating equation does not account for patient fixed effects, as doing so would restrict the measure of practice style to only those patients who have moved between practices. This is not feasible in our setting because we observe only a subset of GP practices. Nor is it desirable, as focusing on movers would limit the representativeness of our sample.

[14] In Appendix Figure A.4, we show that this time-invariant measure is strongly correlated with an alternative time-varying measure based on a 3-year interval, indicating that our measure effectively captures consistent prescribing patterns over time.

Figure 3: Propensity to prescribe benzodiazepines



Notes: The figure plots the histogram of the estimated propensity to prescribe benzodiazepines (x-axis and left y-axis). A local-linear regression of the predicted probability of being prescribed benzodiazepines on the GP practice propensity after the residualization (described in Equation (1)) is overlaid and displayed on the right y-axis. 95% confidence bands are also shown. Source: authors' calculations using Nivel and Statistics Netherlands microdata.

Figure 3 shows that the estimated practice propensity to prescribe benzodiazepines, pp_i^j, varies considerably across GP practices, providing valuable variation to examine the role of practice style on patient outcomes. A local linear regression of the fitted probability of being prescribed benzodiazepines on practice propensity to prescribe is overlaid. It shows that this association is quite strong and approximately linear. In particular, a one-point increase in the index, i.e., the difference between the 10^{th} and 90^{th} percentiles of the distribution, corresponds to an almost 1.5 percentage point increase in the (residualized) probability of being prescribed benzodiazepines.

4.2 Dynamic Difference-in-Differences

We use a dynamic staggered difference-in-differences model with individual and year-fixed effects to evaluate the effect of GP propensity to prescribe on health and labor market outcomes. Event time is defined as the number of years away from the loss of a relative, representing a potential trigger for a mental health issue. We focus on a time window of 11 years, from four years before up to six years after the loss of a relative.

Formally, we estimate the following equation:

$$Y_{it} = \beta_i + \beta_t + \beta_{agebins} + \sum_{k=-3^+}^{6} \delta^k \tau_{it}^k + \sum_{k=-3^+}^{6} \gamma^k \tau_{it}^k \cdot pp_i^j + \xi_{it} \tag{3}$$

The outcome Y_{it} represents the health or labor market outcome for individual i at time t, τ_{it}^k is a dummy variable that identifies the time away from the shock (at $k = 0$ and $k \neq -1$), and pp_i^j represents the propensity to prescribe benzodiazepines of the practice j. Since all individuals experience the shock, we bin the fourth and third years before the shock ($k = -3^{+}$) to avoid collinearity with time fixed effects (Borusyak et al., 2024).

The coefficients of interest are the interaction terms between event time dummies, and the propensity to prescribe indicators, γ^ks: they should be interpreted as the effect on Y_{it} when moving from a practice at the 10th percentile to a practice at the 90th percentile. The effects are for each event time k relative to one calendar year before the shock, i.e. $k = -1$. Equation (3) also includes year and individual fixed effects, α_t, α_i respectively, and a full set of five-year age bins $\beta_{agebins}$. Standard errors are clustered at the level of the GP practice they had at the time of their loss to account for the potential correlation of patients' characteristics within the same GP practice.

4.3 Identifying Assumptions

Here, we outline the three core assumptions for staggered DiD models—parallel trends, no anticipatory behavior, and homogeneous treatment effects—and introduce an additional assumption of quasi-random patient assignment to GP practices. We then consider how GP prescribing propensity could reflect a broader practice style and describe how we address this concern in our analysis.

Parallel trend assumption. To ensure the parallel trend assumption, we employ two sample selection criteria and make an additional assumption. We restrict the sample to (i) individuals who experience a common exogenous mental health shock (i.e., the death of a close relative) and (ii) the implementation of a four-year washout period for mental health drugs and diagnoses to avoid the pre-treatment effect of the GP. This second restriction follows the fact that approximately 15% of the individuals experiencing the death of a close relative had some previous interaction with the GP practice for mental health issues (either a diagnosis or a benzodiazepine prescription, see Figure 2).[15] However, even with an exogenous trigger like the death of a close relative and by selecting patients without prior mental health problems in the pre-period, the assumption of parallel trends in the post-period might not hold if patients' characteristics differ across practices with different propensities to prescribe. Such differences could lead patients to react differently to the shock. Therefore, we introduce an additional assumption: the conditional quasi-random assignment of patients to practices. While not strictly required in a DiD setting, this assumption enhances the credibility of our research design.

Conditional quasi-random assignment of patients to practices. Concerns about selection are limited because patients in the Netherlands have limited (or no) choice of GP once they fix their place of residence, effectively constraining them to the practices operating in their specific location (Currie and Zwiers, 2023 and Table 1). Thus, any selection concerns should be largely mitigated once we account for location fixed effects.

We assess whether it is reasonable to assume quasi-random assignment of patients to practices with different propensity to prescribe benzodiazepines, conditional on neighborhood fixed effects. Specifically, we

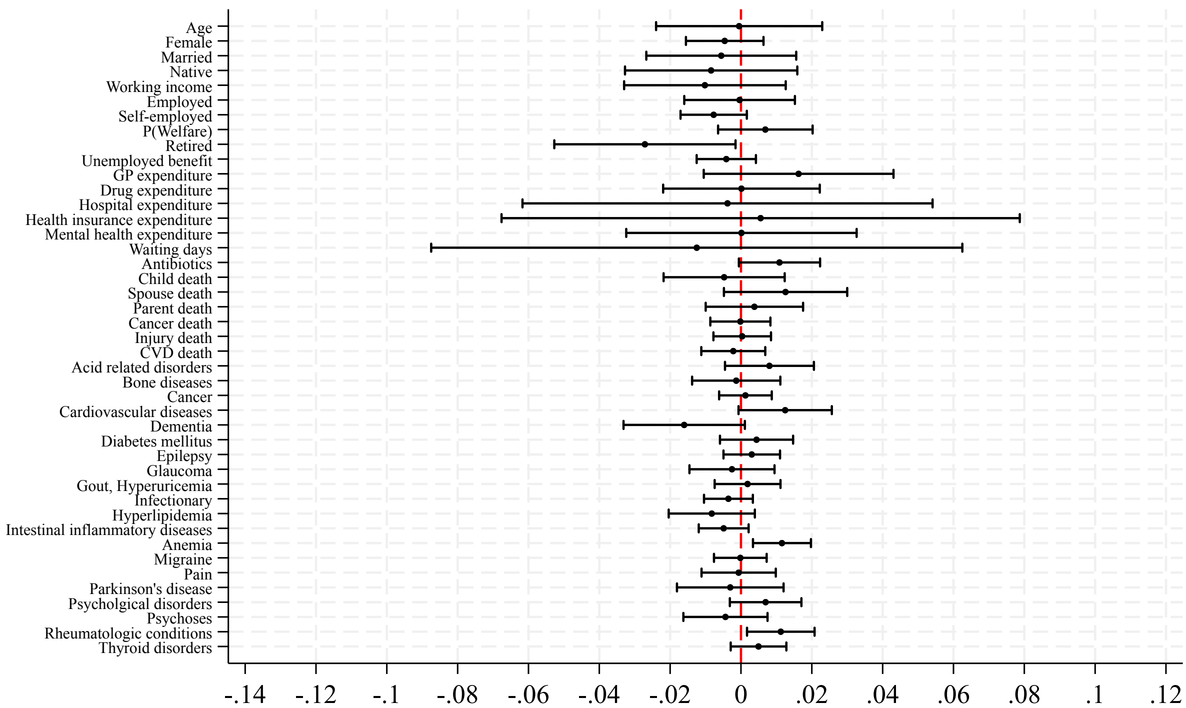
[15]The four-year washout period for benzodiazepine use and diagnoses cannot be observed for all patients in the GP data due to limitations in GP practice coverage. This results in a washout period that varies between one and four years (3.37 years on average).

use a rich set of demographic, health, and labor market characteristics from the year before the relative's loss, including dispensed medications recently used by Danesh et al. (2024) to build a chronic conditions index that strongly predicts mortality and health inequalities over the life cycle.

Figure 4 summarizes the results of regressing our (residualized) practice propensity to prescribe (as in Equation 2) on these patient characteristics. For comparability, all coefficients have been standardized. The Figure shows that—in our working sample—patients appear to be as randomly assigned to their GP practice. In particular, all the coefficients are small and not statistically different from zero. Consequently, the joint F-statistic does not reject the hypothesis that all coefficients equal zero (p-value above 10%).

In the Appendix, we replicate this balancing test using an *unconditional* measure of prescribing propensity (i.e., the share of patients with at least one benzodiazepine prescription). Although we detect a few marginal correlations, they are modest in magnitude (Figure A.5). We also show that once we include only neighborhood fixed effects (without the other demographic controls used in Equation (2)), these small unconditional differences disappear, reinforcing the plausibility of quasi-random patient assignment to GPs (Figure A.6).

Figure 4: Balancing test



Notes: This figure tests for random assignment of GP practice to patients based on a large set of observable characteristics in the year before the death of a close relative (event time -1). Specifically, we regress our residualized measure of GP propensity to prescribe benzodiazepine on patient socio-demographics characteristics, labor market outcomes, and previous medical history. The F-test statistic is 1.26 and the p-value is 0.1286. For comparability purposes, all regressors have been standardized. Regression coefficients and their accompanying 95% confidence intervals are plotted. Robust standard errors are clustered at the GP practice level. Source: authors' calculations using Nivel and Statistics Netherlands.

As a robustness check, Table A.4 compares patients who are assigned to GPs in the first versus the third tercile of our residualized propensity measure, again in the year before bereavement. Standardized differences across the two groups remain below 0.04 standard deviations for all characteristics considered. Taken together, these findings strongly support the assumption of quasi-random assignment of patients to practices with differing prescribing styles, once location is held fixed.

In a further robustness check, we weaken the quasi-random assignment assumption by constructing an alternative measure of the propensity to prescribe benzodiazepines that only exploits the GP's prescribing response after the death of a close relative. Specifically, we replace Equation (1) with the following estimation:

$$Prescribed_{ijt} = \gamma_0 + \gamma_{1j} GP_j + \gamma_{2j} GP_j * Postdeath_{it} + \gamma_t + \gamma_w + \theta X_{it} + v_{ijt} \tag{4}$$

In this equation, we add a full set of GP practice fixed effects, GP_j, and interaction terms between these practice fixed effects and an indicator variable $Postdeath_{it}$, which equals one for individuals who experience the death of a relative and are in the post-shock period. The coefficients on these interaction terms, γ_{2j}, capture the GP's prescribing behavior with affected patients above and beyond their typical prescribing patterns. We then use these coefficients to construct our alternative propensity to prescribe measure, instead of aggregating the residuals from Equation (1). In other words, we allow patients to be aware of (and potentially select based on) the GP's general prescribing behavior, but we assume they cannot predict the GP's change in prescribing behavior following a relative's death. While this second approach requires a weaker assumption, it comes at a cost in terms of increased noise: it discards valuable variation by focusing only on the post-period change in GPs' prescribing behavior.

Anticipation. While the death of close relatives is generally unanticipated, there may be cases where anticipation occurs. In our context, it is sufficient that any anticipation does not translate into differences in healthcare use or GP treatment across patients enrolled in practices with varying propensity to prescribe benzodiazepines. Moreover, such anticipation is unlikely to significantly affect our results because we restrict our sample to patients with no previous mental health treatment or diagnosis in the previous four years and thus rule out that the mental health effects of a sick or dying relative were large enough to warrant a doctor visit. As a robustness check, we exclude cancer-related deaths, which are often anticipated, to ensure our findings are not driven by anticipated deaths (see Figure A.7).[16]

Homogeneous Treatment Effects. Recent literature on staggered DiD has proposed alternative estimators to avoid the bias that might arise in the presence of treatment effect heterogeneity across cohorts. In our case, even in the presence of a potential bias in the event study coefficients, this heterogeneity should not lead to a biased estimate of the γ^ks, the coefficients on the interaction terms with the propensity to prescribed benzodiazepines, provided that the quasi-random assignment of patients to practices assumption holds. In other

[16]More generally, van den Berg et al. (2017), who studies the effect of child deaths on their parents' health and economic trajectories, show that differences in outcomes after the shock are driven by pure grief rather than whether the death was anticipated or not.

words, the estimated differences across patients treated by practices with a different propensity to prescribe benzodiazepines should be valid even if the baseline event-time coefficients are biased.[17]

However, to better understand if the effect comes from changes in the outcomes of patients of high-prescribing or low-prescribing GPs after the death of the relative, we also run separate estimates by tercile of the distribution of the propensity to prescribe benzodiazepines using the estimator proposed by Sun and Abraham (2021). This allows us to avoid potential bias in the event study coefficients. Implementing this estimator requires us to add a control group of untreated individuals, or to use the last treated cohort (i.e., 2016) as an untreated group. This second approach would result in an extremely unbalanced sample in event time, as only earlier cohorts would be used to estimate long-term effects, and it would mechanically reduce our observation window by one year (because we can no longer use observations after 2015). For this reason, we follow the first strategy by using a stratified random sample of 100,000 patients enrolled in Nivel GP practices that matches the age distribution of our estimation sample.

Results interpretation.

The last concern is that our estimated effects might be capturing the influence of other aspects of GP practice style, which could affect the interpretation of our results. We address this concern in three ways: *i*) We investigate the relationship of GP propensity to prescribe benzodiazepines with the prescription of other medications that might contribute to the estimated effects, such as opioids and antidepressants. *ii*) We conduct a robustness test by focusing on antibiotics, which is another class of drugs where overprescription is common, and construct a propensity-to-prescribe measure based on this medication. *iii*) We investigate the heterogeneity of our results by age, sex, and tercile of the propensity to prescribe benzodiazepines, to check for consistency in the effects on benzodiazepine prescriptions and labor market outcomes.

5 Results

In this section, we present the empirical findings of our study on the impact of GPs' benzodiazepine prescribing behavior following a significant mental health shock: the death of a close relative. We begin by examining the effects on benzodiazepine use and secondary mental health care utilization. Subsequently, we analyze the downstream consequences on patients' labor market outcomes.

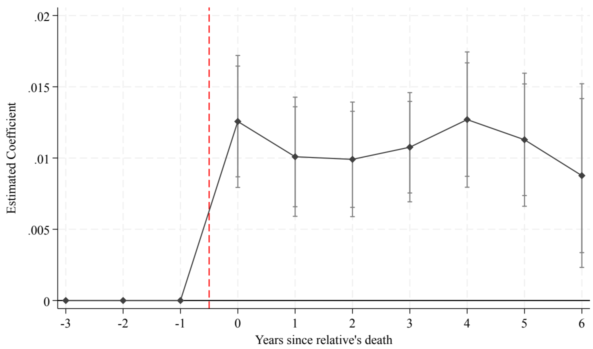
5.1 Benzodiazepine Use and Secondary Mental Health Care

Figure 5 reports the event study results for different measures of benzodiazepine prescriptions and secondary mental health expenditure. Specifically, we present the estimated coefficients of interest, $\gamma^k s$, which are the interaction terms between the estimated propensity measure and the event time dummies using the conventional two-way fixed effects estimator.

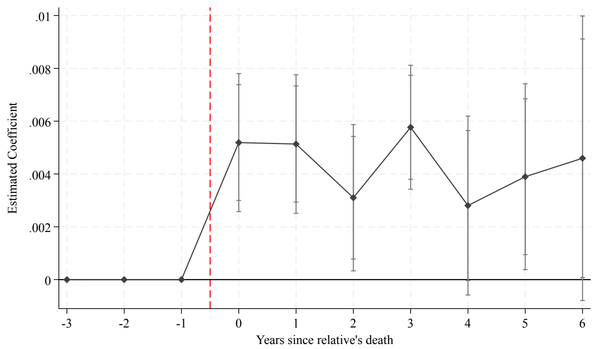
[17] Moreover, none of the newly proposed estimators for staggered DiD allows for direct interaction terms.

Figure 5: Benzodiazepine use and secondary mental health care

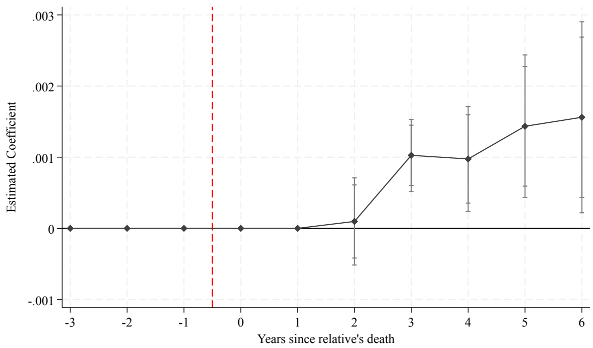
(a) Benzodiazepine prescriptions



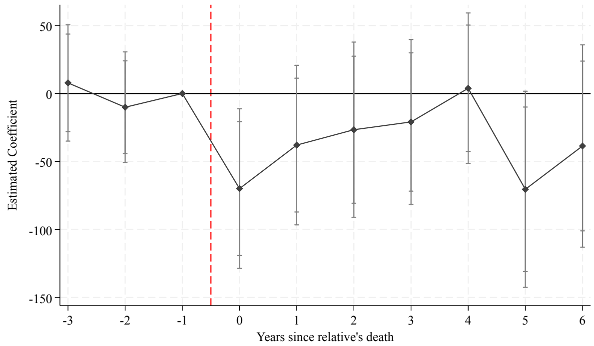
(b) Red flag prescriptions



(c) Six prescriptions per year for three consecutive years



(d) Secondary mental health care expenditure



Notes: For each event time, the figure displays the estimates of the γ_k coefficients reported in Equation 3, namely the estimated difference in the probability of receiving a: (a) benzodiazepine prescription; (b) a red flag prescription; (c) 6 prescriptions per year for three consecutive years; (d) secondary mental health care expenditure resulting from a one unit increase in the propensity to prescribe benzodiazepines. We report 90% and 95% level confidence intervals (standard errors clustered at the practice level). N =580,840 patient-years, for benzodiazepine outcomes (a–c) and N =704,257 for secondary mental health care. Source: authors' calculations using Nivel and Statistics Netherlands microdata.

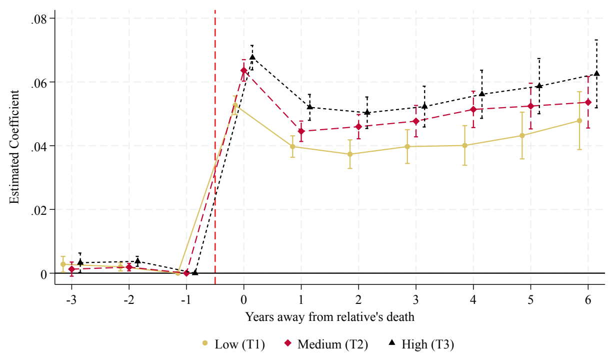
A higher propensity to prescribe benzodiazepines (from the 10th to the 90th percentiles) leads to a significantly increased probability of patients receiving benzodiazepine prescriptions after the death of a relative, with effects lasting at least six years (Panel (a)). The effect size, slightly above one percentage point, represents almost a third of the average increase in benzodiazepine prescriptions observed in the sample after the relative death. Most importantly, many of these additional prescriptions are potentially inappropriate, as they often deviate from Dutch guidelines (Panel (b)).[18] Furthermore, a high propensity to prescribe benzodiazepines also leads to increased intensive and persistent use (Panel (c)). Specifically, the estimated difference in the probability of receiving at least six prescriptions per year for three consecutive years reaches 0.2 percentage points

[18] In Figure A.8, we report the results for each of the four Red-flag prescriptions.

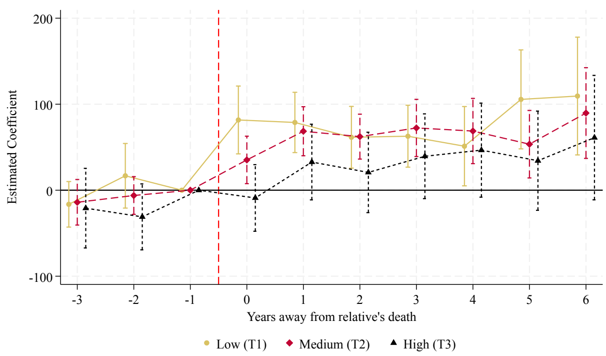
after six years.[19] While this number may appear small, it is substantial given that the population mean use is 0.8% and almost entirely driven by patients aged 70 and above, whereas our sample consists of younger, benzodiazepine-naive patients.

Finally, in Panel (d) we show that increased benzodiazepine prescriptions by high-prescribing GP practices are accompanied by lower mental health care expenditures among their patients during the first two years following the death of a relative. This finding implies that doctors who tend to prescribe more benzodiazepines refer fewer patients to mental health specialists. For completeness, Figure A.9 shows no significant differences in other healthcare expenditure components among patients enrolled in GP practices with varying propensities to prescribe benzodiazepines after the shock.

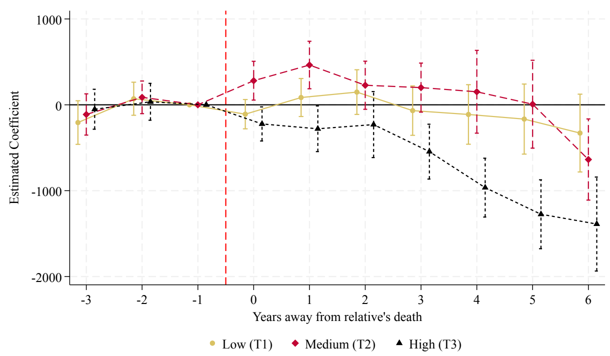
Figure 6: Sun and Abraham estimates by tercile of the propensity to prescribe benzodiazepine



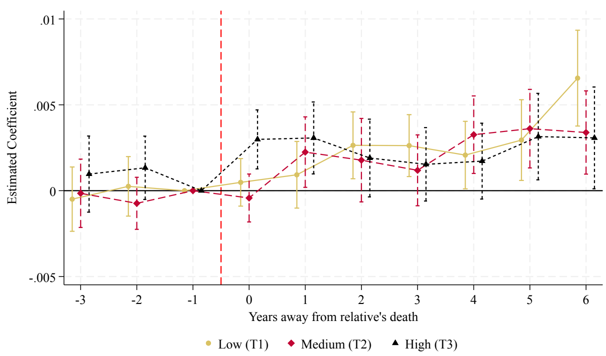
(a) Benzodiazepine prescriptions



(b) Mental health care expenditure



(c) Income from work



(d) Probability of unemployment benefits

Notes: For each event time, the figure displays the estimate of the event study coefficients (δ_k reported in Equation 3 without interaction terms) using the Sun and Abraham estimator running separated estimates by tercile of the propensity to prescribe a benzodiazepine. We show the result for the following outcomes: a) probability of a benzodiazepine prescription ($N = 580,840$), b) Mental health care expenditure ($N = 704,257$), c) Income from work (N =740,588), and d) probability of unemployment benefits (N =746,069). We report 90% and 95% level confidence intervals (standard errors clustered at the practice level). Source: authors' calculations using Nivel and Statistics Netherlands microdata.

[19] Note that, in the first two years after the shock, the difference across groups is zero by construction.

This interpretation becomes clearer when we compare the trajectories of patients by terciles of their GP's propensity to prescribe benzodiazepines, as estimated using the Sun and Abraham method (Figure 6).[20] Although benzodiazepine uptake rises proportionally across terciles of the GP's prescribing tendency (Panel (a)), mental health care expenditures follow a non-linear pattern (Panel (b)). Specifically, patients whose GPs fall in the lowest tercile (i.e., the 33% least likely to prescribe benzodiazepines) incur almost 100 euros more in mental health care costs immediately following the death of the relative. This increase corresponds to 66% of their pre-period mean and 30% of the overall sample mean annual expenditure. A similar pattern, if we exclude the year of the shock, is also observed for patients in the middle tercile. In contrast, those enrolled in the highest prescribing tercile experience no significant increase in mental health care use following a relative's death. These results imply that while high-prescribing GPs tend to rely solely on benzodiazepine–based treatment, lower- and middle-prescribing GPs respond to a mental health shock by increasing referrals to specialized care, thereby driving the observed differences in mental health care expenditures reported in Figure 5.

5.2 Labor market outcomes

Figure 7 shows that individuals treated by high-propensity GP practices (i.e., moving from the 10th to the 90th percentile) experience a decline in income, peaking at nearly 1,000 Euro (approximately 4% of the pre-mean yearly income) after five years. In the figure, we also mark with a solid line the cumulative effect that reaches 3,000 Euro after six years.[21] Panels (b) and (c) of Figure 7 provide insight into the sources of the estimated income decline. Individuals treated by a high-propensity GP practice are more likely to receive unemployment benefits in the first two years. From the third year onward, the wage rate is lower, reaching a difference of 40 cents per hour by the fourth year. When annualized, this lower wage rate accounts for approximately 70% of the estimated difference in work-related income presented in Figure 7. These results align with the structure of the Dutch welfare system, which provides generous unemployment benefits for up to two years to individuals with sufficient seniority who lose their jobs. Consequently, there is little evidence of significant income and wage declines in the first two years. However, upon re-entering the labor market, individuals experience reduced wage rates.

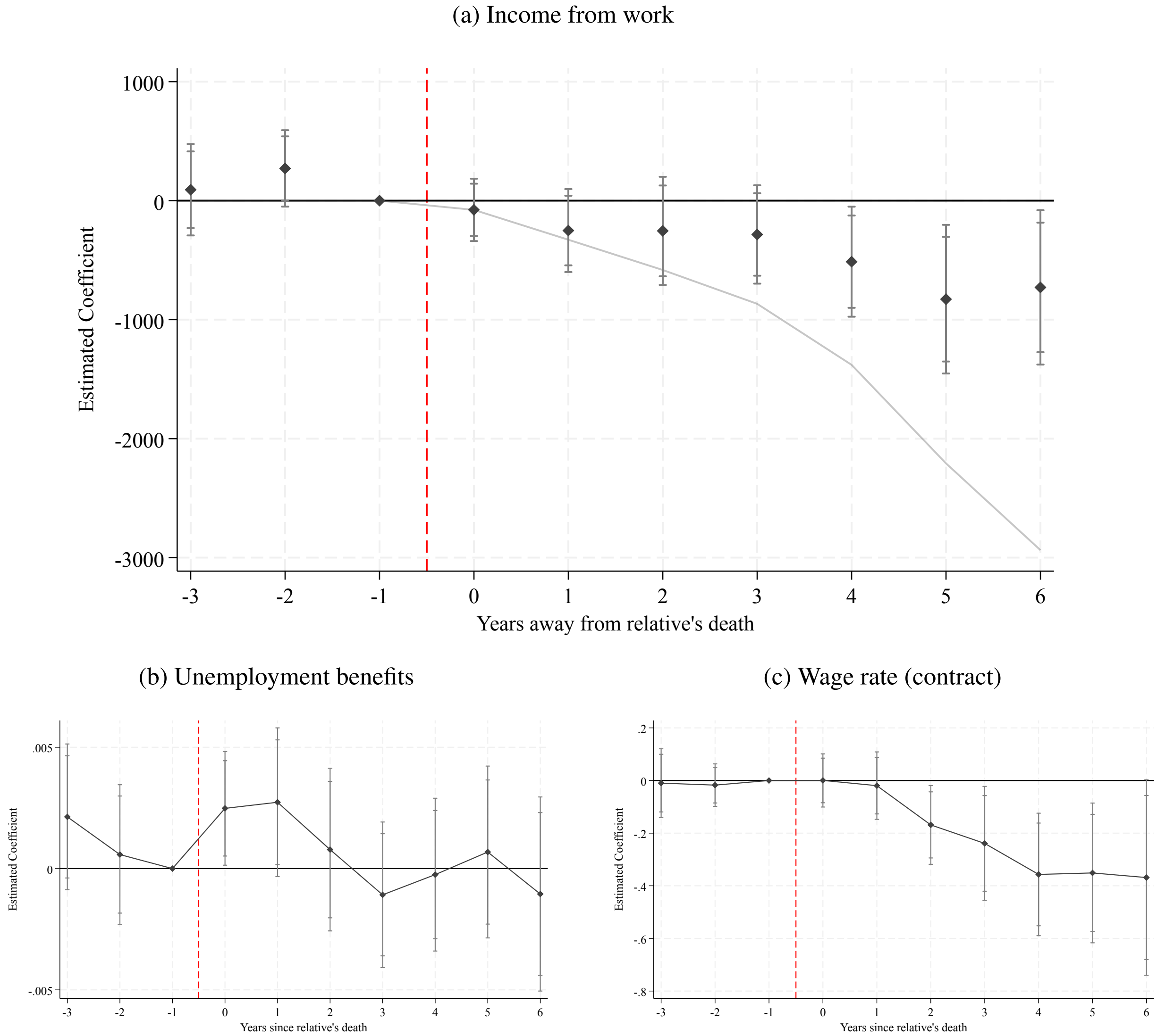
As before, the comparison of trajectories by tercile of the propensity to prescribe distribution provides interesting insights. We find that the negative labor market consequences of bereavement are concentrated among patients treated by GPs in the third tercile (Panels (c) and (d) of Figure 6). For these patients, income starts to significantly decline already in the first two years, and unemployment benefit receipt increases by almost 0.4 percentage points in the first two years following the shock, representing a 25% increase relative to the pre-period mean. Similar to figure 7, the estimated income drop (with respect to the pre-period) becomes

[20] In Appendix A.10 we show the raw trends that confirm that the estimated differences across terciles are evident in unconditional trends.

[21] Figure A.11 shows that the estimated income drop after 5 years is even larger (-6%) if we use the logarithm of income as the outcome variable.

more apparent over time and reaches almost 1,500 Euro 6 years after the shock.

Figure 7: Effects on labor market outcomes



Notes: For each event time, this figure shows the estimated γ_k coefficients from Equation 3. Specifically, it illustrates the estimated difference in (a) income from work (N = 740,588) (b) probability of receiving unemployment benefits (N = 746,069); and (c) wage rate (N = 379,178) in the work contract resulting from a one-unit increase in the propensity to prescribe benzodiazepines. We report 90% and 95% level confidence intervals (standard errors clustered at the practice level). In Panel (a), the continuous gray line represents the cumulative impact on income from work, calculated by summing all γ_k coefficients up to each event time q. Source: authors' calculations using Nivel and Statistics Netherlands microdata.

Conversely, we do not observe any significant income loss for people treated by doctors in the other two terciles, with the exception of a significant drop in the sixth year for the middle tercile. This pattern is in line with the findings on mental health care expenditure, where only patients in the third tercile do not experience an increase in specialized mental health care after the shock, relying only on benzodiazepine-based treatment. In the Appendix, we show that the probability of intensive and persistent use is also concentrated among patients in GP practices in the third tercile of the prescribing propensity (Figure A.12).

Heterogeneity. We further explore the heterogeneity of our results across two key dimensions: age and sex. Table 3 presents the results for each subgroup, with estimates provided separately for short-term (0–1 years), mid-term (2–4 years), and long-term (5–6 years) effects.[22] Individuals under 50 treated by GP practices with a higher propensity to prescribe benzodiazepines experience consistently lower mental health care expenditures throughout the post-period. In contrast, for those over 50, no significant differences are observed based on the GP practice's prescribing propensity. The negative impact on work income is also more pronounced for individuals under 50, suggesting that younger patients face greater labor market consequences when treated by GPs with a higher propensity to prescribe benzodiazepines.

When examining gender differences, we find that the increase in benzodiazepine prescriptions driven by more lenient GPs is larger for females than for males. However, males treated by high-prescribing GPs exhibit lower mental health care expenditures.

Overall, patients treated by GP practices with a higher propensity to prescribe benzodiazepines are more likely to receive benzodiazepine prescriptions and less likely to be referred for specialized mental health care. This treatment pattern leads to increased persistent and long-term benzodiazepine use and adverse labor market outcomes. These effects are observed exclusively among patients treated by the 33% of GPs with the highest prescribing propensity, and especially pronounced among younger individuals (under 50) and males. Subgroups with more pronounced labor market effects also use less specialized mental health care and exhibit higher rates of persistent and long-term benzodiazepine use, highlighting a clear and consistent pattern. We cannot exclude that the observed heterogeneity across gender and age may also reflect broader labor market differences. For instance, females are more likely to work part-time, potentially mitigating the negative consequences on earnings or employment status. Likewise, early-career interruptions can have more severe long-term consequences for younger workers than for those nearing retirement (e.g., Sullivan and Von Wachter, 2009), which may account for the stronger negative outcomes we document in younger workers. It is also worth mentioning that younger people are especially vulnerable to misuse and addiction (e.g., Böckerman et al., 2024), a result that is consistent with our evidence on prolonged and persistent use of benzodiazepine.

[22] In the Appendix we report the corresponding event study figures to check for pre-trends (Figure A.13 and Figure A.14).

Table 3: Results by Gender, and Age

	Benzodiazepines		Mental health care exp.		Income		Unemp. Benefits	
Panel A: All								
Short (0–1 yrs)	0.0127***	(0.0018)	-53.92**	(25.76)	-163.89	(136.77)	0.0026**	(0.0012)
Medium (2–3 yrs)	0.0125***	(0.0015)	-16.10	(26.89)	-349.04*	(188.21)	-0.0002	(0.0014)
Long ($\geq$ 4 yrs)	0.0115***	(0.0020)	-58.02*	(32.71)	-783.47***	(293.84)	-0.0001	(0.0017)
N	580,840		704,257		740,588		746,069	
Panel B: Gender								
Male								
Short (0–1 yrs)	0.0105***	(0.0019)	-69.03*	(40.65)	-268.22	(226.81)	0.0039**	(0.0019)
Medium (2–3 yrs)	0.0104***	(0.0016)	-33.44	(38.19)	-605.65*	(329.01)	0.0026	(0.0022)
Long ($\geq$ 4 yrs)	0.0098***	(0.0029)	-98.64**	(44.98)	-1348.96***	(434.38)	0.0019	(0.0025)
N	304,585		369,251		387,781		391,262	
Female								
Short (0–1 yrs)	0.0148***	(0.0028)	-37.40	(28.41)	-57.31	(125.26)	0.001	(0.0019)
Medium (2–3 yrs)	0.0145***	(0.0026)	2.91	(34.67)	-97.27	(199.61)	-0.0033	(0.0020)
Long ($\geq$ 4 yrs)	0.0130***	(0.0039)	-13.06	(49.18)	-222.51	(294.37)	-0.0023	(0.0024)
N	276,255		335,006		352,807		354,807	
Panel C: Age								
Young (<50)								
Short (0–1 yrs)	0.0134***	(0.0022)	-89.87**	(37.82)	-172.63	(163.37)	0.0019	(0.0017)
Medium (2–3 yrs)	0.0114***	(0.0019)	-63.54	(42.71)	-365.55	(270.28)	-0.0011	(0.0017)
Long ($\geq$ 4 yrs)	0.0084***	(0.0032)	-110.34**	(46.52)	-1036.67**	(454.54)	-0.0016	(0.0020)
N	318,855		390,369		409,487		413,297	
Old (50+)								
Short (0–1 yrs)	0.0117***	(0.0023)	-13.60	(28.49)	-176.16	(227.24)	0.0036	(0.0023)
Medium (2–3 yrs)	0.0137***	(0.0024)	46.62*	(24.09)	-346.41	(295.02)	0.001	(0.0028)
Long ($\geq$ 4 yrs)	0.0158***	(0.0033)	15.60	(39.13)	-447.64	(406.96)	0.0018	(0.0032)
N	261,985		313,888		331,101		332,772	

*Notes: The table presents the estimated effects of a one-unit increase in the propensity to prescribe benzodiazepines, as specified in Equation (3), on four outcomes: the probability of receiving a benzodiazepine prescription (Benzodiazepines), mental health care expenditures (Mental health care exp.), work-related income (Income), and unemployment benefits (Unemp. Benefits). For clarity, the γ_k coefficients from the post-period are aggregated into three time frames: short-term (0–1 years), mid-term (2–3 years), and long-term (> 4 years). The results are presented in three panels: Panel A reports estimates for the whole sample, Panel B separates estimates by gender, and Panel C separates estimates by age group. Significance levels: *** $p < .01$, ** $.01 \leq p < .05$, * $.05 \leq p < .10$. Source: authors' calculations using Nivel and Statistics Netherlands microdata.*

5.3 The role of mental health nurses

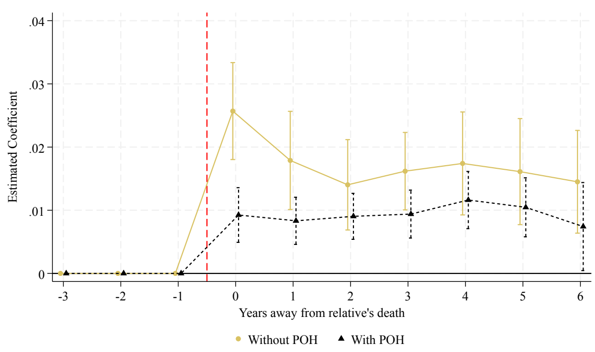
We next investigate whether the introduction of mental health nurses in GP practices can moderate the negative consequences of high benzodiazepine prescribing. As described in Section 2, visits to a mental health nurse have been covered by public health insurance since 2008. Mental health nurses provide therapy, counseling, or low-intensity cognitive-behavioral therapy, thereby reducing the GP's workload and offering an alternative to prescribing benzodiazepines for mild mental health problems.

To evaluate their role, we exploit the staggered hiring of mental health nurses across GP practices. In particular, we compare patients enrolled at a practice that had employed at least one mental health nurse at the time of the loss of a relative to patients enrolled at a practice that did not employ a mental health nurse at the time of the shock. Even within the same practice, patients may be treated differently depending on whether their bereavement occurred before or after the mental health nurse was employed. Since our strategy requires that the timing of the introduction across practices is not correlated with their propensity to prescribe, in Figure A.15 we show that there are no systematic differences in the adoption of mental health nurses across terciles of our propensity to prescribe benzodiazepines.

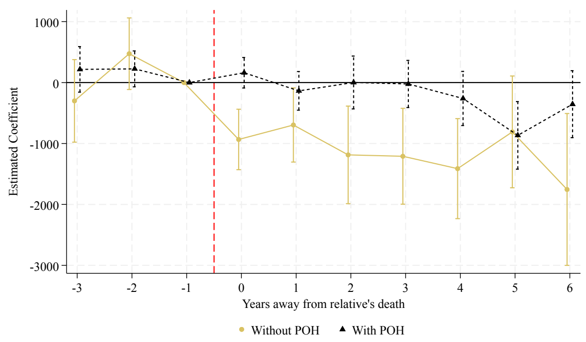
Figure 8 illustrates how the main effects of high- versus low-prescribing GP practices (90th vs. 10th percentile) on benzodiazepine use and labor income vary by whether a nurse was present at the time of a relative's death. We find that the gap in benzodiazepine prescriptions between high- and low-prescribing practices is approximately halved in the presence of a mental health nurse. Consistent with this reduction in prescribing, the negative labor market effects of enrolling in a high-prescribing practice also shrink substantially.

Figure 8: Effects on benzodiazepine prescription and income by POH availability

(a) Benzodiazepine prescriptions



(b) Income from work



Notes: For each event time, this figure shows the estimated γ_k coefficients from Equation 3. Specifically, it illustrates the estimated difference in (a) benzodiazepine prescription ($N = 580{,}840$) (b) income from work ($N = 740{,}588$) resulting from a one-unit increase in the propensity to prescribe benzodiazepines. We report 90% and 95% level confidence intervals (standard errors clustered at the practice level). Source: authors' calculations using Nivel and Statistics Netherlands microdata.

These findings suggest that providing basic non-pharmacological therapy within primary care settings can serve as a viable alternative to benzodiazepine treatment and alleviate the associated long-term economic costs for patients. In the Appendix, we show that these results are robust to potential selection and cohort effects. We show that our results hold when restricting the sample to patients who experience bereavement within three years before or after the nurse is hired (Figure A.16). Moreover, since most of the events without a mental health nurse employed are concentrated at the beginning of the observation period, we replicate the main findings focusing solely on early cohorts (2011–2013) obtaining similar estimates (Figure A.17).

5.4 Alternative Mechanisms

To study if the effects that we observe may, at least in part, be influenced by other aspects of GP practice style correlated with their propensity to prescribe benzodiazepines, we explore alternative mechanisms.

First, we examine whether GPs with a higher propensity to prescribe benzodiazepines also prescribe more of other drugs. In Figure A.18, we analyze two main psychotropic drug categories: (i) antidepressants, the other primary pharmacological treatment for mental health conditions, and (ii) opioids, medications primarily intended for pain management but associated, especially in the United States, with mental and social issues and adverse health and labor market outcomes.

The GP practice propensity to prescribe benzodiazepine is not related to increased antidepressant use. However, opioid use increases, but only after three to four years following the relative's death, mirroring the pattern of persistent, long-term benzodiazepine use depicted in Figure 5. This delayed increase suggests that the initial rise in benzodiazepine use and the subsequent deterioration in health and labor market outcomes may lead these individuals to develop additional health problems that necessitate opioid prescriptions. Therefore, the increase in opioid use is more likely a consequence rather than a cause of the observed negative outcomes.

Second, we construct an alternative GP propensity to prescribe antibiotics. We choose antibiotics for two reasons: (i) high antibiotic prescribing rates are often associated with poor practice styles and suboptimal diagnostic skills (e.g., Chan et al., 2022; Meeker et al., 2016), making it a potential proxy for overall practice quality; and (ii) although patient characteristics are balanced across practices, we find a small but significant association between the propensity to prescribe benzodiazepine and antibiotic use in the pre-period (see Figure 4). We find that the effects of a high propensity to prescribe antibiotics are substantially smaller (Figure A.19) than those reported for benzodiazepines in Figure 5a and are not consistently statistically significant. This lack of significant findings suggests that our main results are not driven by a general poor practice style but are specific to benzodiazepine prescribing behaviors.

Third, we study the impact of wealth effects, e.g., an inheritance after the loss of a relative, might influence labor market participation and thus explain our results. However, for this mechanism to be plausible, there would need to be a positive correlation between the GP practice propensity to prescribe benzodiazepines and inheritances, which contradicts our assumption of the quasi-random assignment of patients to GP practices. We still test for this possibility by examining changes in income from capital and real estate around the event time. The results in Figure A.20 show that there is no relationship between the GP practice propensity to prescribe benzodiazepines and changes in wealth-related income sources.

Fourth, we test whether regional waiting times could drive our results. Prudon (2023) shows that longer regional waiting times negatively impact labor market outcomes by delaying access to mental health specialists for individuals with depression. Waiting times may be an alternative explanation for the negative effect of GP practice propensity to prescribe causes on mental health care expenditures if waiting times and the propensity are correlated. Yet, we find no correlation between the propensity to prescribe benzodiazepines and municipality-level data on waiting times from Prudon (2023) at the time of the loss or in the pre-period (Table A.5).

5.5 Robustness checks

In this section, we investigate the robustness of the results to five potential violations of the identifying assumptions. First, we implement two robustness checks related to the assumption of exogenous sorting of patients to GP practice. As described in Section 4, we construct an alternative propensity-to-prescribe measure that relies on weaker assumptions regarding patient allocation to GP practices. This alternative measure allows patients to potentially select their GP based on their propensity to prescribe benzodiazepines. Still, it assumes that patients cannot predict their GP's change in prescribing behavior when a relative dies. The results depicted in Figure A.21 are qualitatively consistent with the main results. We observe more pronounced effects on benzodiazepine prescriptions and a more substantial but more noisy decrease in income associated with a larger GP propensity to prescribe benzodiazepines. Also, the effects on mental health care expenditure and unemployment appear to be noisier. Since this alternative propensity measure relies on less variation than the measure used in the main text, we are not surprised to find increased noise in our estimates. Finally, also related to the concern of endogenous sorting, we show that our results are not driven by the few patients living outside their GP catchment area. In Figure A.22, we show that our estimates are unaffected by the exclusion of people living at least 10 km away from their GP practice.

Second, the death of a relative may be anticipated. As a robustness check, we exclude cancer deaths, which are more likely to be anticipated and represent one of the largest causes of death in our sample. The results reported in Figure A.7 are very similar to those in the main text, except for larger standard errors.

Third, we consider potential heterogeneity by the type of relative who died. However, since over 60% of relative deaths in our sample are deaths of parents, we do not have sufficient power to investigate other types of deaths (e.g., spouses, siblings, and children) separately. Therefore, we conduct two different robustness checks. First, we estimate our model using only parents. Second, we use all types of deaths but include in Equation (3) additional interaction terms between relative death type and event time dummies. In both cases, the results show that our estimates for the effect of the GP propensity to prescribe benzodiazepines are unaffected (Figure A.23 and A.24).

Fourth, we investigate whether our findings could be driven by differential survival across patients by estimating a survival model with patient death as an outcome. The results reported in Table A.6 based on standard survival analysis (under different functional forms) show that there are no differences in the probability of death among individuals treated by GPs with different propensities to prescribe.

Fifth, we perform a permutation test in which we randomly assign placebo deaths to 100,000 patients patients in the Nivel GP data in the same age range as those in our working sample, and estimate Equation 3 on three main outcomes: benzodiazepine prescriptions, mental health care expenditure, and income from work. We repeat this process 500 times, producing a distribution of "placebo" estimates that represents the null hypothesis of no true effect. We then compare our main estimates to these placebo distributions. For benzodiazepine prescriptions and mental health care expenditure, our estimates lie at the extreme tails of the placebo distributions (p-values below 0.01), reinforcing their statistical significance (Figure A.25). For work income, however, the point estimate falls at about the 20th percentile of the placebo distribution because some permutations yield large (in absolute terms) but very imprecise coefficients. Once we account for the standard errors by examining the distribution of the associated t-statistics, the t-statistic for our main estimate is below the 5th percentile (p-value=0.03), reinforcing our confidence in the statistical significance of the main effects that we report.

Finally, concerns about the external validity might arise from the use of a 4-year wash-out period. Figure A.26 shows the main results without this sample restriction. The only clear difference is in the effect on benzodiazepine use, which is much smaller. This is not surprising because now many people in the pre-period were already using benzodiazepines. Yet, we still find large effects of being enrolled in high-prescriber GP practice on the intensive margin and potential addiction.

6 Conclusion

This paper shows that being enrolled in a general practitioner (GP) practice with higher benzodiazepine prescription rates negatively affects patients' long-term healthcare utilization and labor market outcomes following a salient mental health shock: the death of a close relative.

Using a staggered dynamic difference-in-differences design on merged administrative data from the Netherlands, we show that patients under the care of high-prescribing GPs are significantly more likely to receive benzodiazepine prescriptions. Many of these prescriptions are not in line with Dutch guidelines, especially those restricting long-term use, raising concerns about potentially inappropriate prescribing practices. Furthermore, a higher propensity to prescribe benzodiazepines is related to higher rates of persistent, long-term use of benzodiazepines and higher rates of opioid prescriptions.

Moreover, these patients are more likely to be treated within the GP practice and receive less care from mental health specialists. This pattern is associated with increased benzodiazepine use in the medium to long term and adverse labor market outcomes, including higher unemployment benefits in the short term and significant declines in earnings driven by reduced wage rates in the longer term. The consistency of our results across various analyses underscores the substantial impact of GP prescribing behaviors. The long-term decline in work income from being enrolled in a high-prescribing GP practice after the death of a close relative is comparable to the scarring effects documented for job displacement. Our estimates of earning losses grow over time and stabilize at around 4–6% after five years. This magnitude aligns with findings on job displacement from Norway (Huttunen et al., 2011), which, like the Netherlands, has a generous welfare system. Our estimated effects are, however, smaller than the effect of a one-month increased waiting time reported by Prudon (2023), possibly because of a difference in the severity of the mental health problems of the marginal patient.

The negative labor market effects are particularly pronounced among patients treated by the tercile of GP practices with the highest propensity to prescribe benzodiazepines, by younger individuals, and males; groups where we also observe larger increases in benzodiazepine prescriptions and lower mental health care expenditures. Furthermore, the presence of a mental health nurse in the GP practice halves the difference in benzodiazepine prescription rates and reduces the labor market effects.

From a policy perspective, our findings suggest that the GP practice propensity to prescribe benzodiazepines has significant long-term implications for patients' well-being and economic productivity. As healthcare systems in many countries face supply constraints and cost pressures, there is a trend toward shifting away from specialized mental health care, such as psychotherapy, in favor of treatment in a primary care setting, including drug treatments. While benzodiazepines may be effective in the short run, our results indicate that benzodiazepine prescriptions may lead to suboptimal outcomes for the marginal patients receiving this medication. Moreover, the results on the role of the mental health nurse suggest that these employees may help to limit benzodiazepine prescriptions by lowering the barrier to seek alternative treatment, including therapy. To address the issues highlighted in this paper, policymakers should seek to understand why GPs deviate from clinical guidelines and implement measures that deal with these underlying reasons to promote adherence to clinical guidelines and to encourage appropriate referrals to specialized mental health services.

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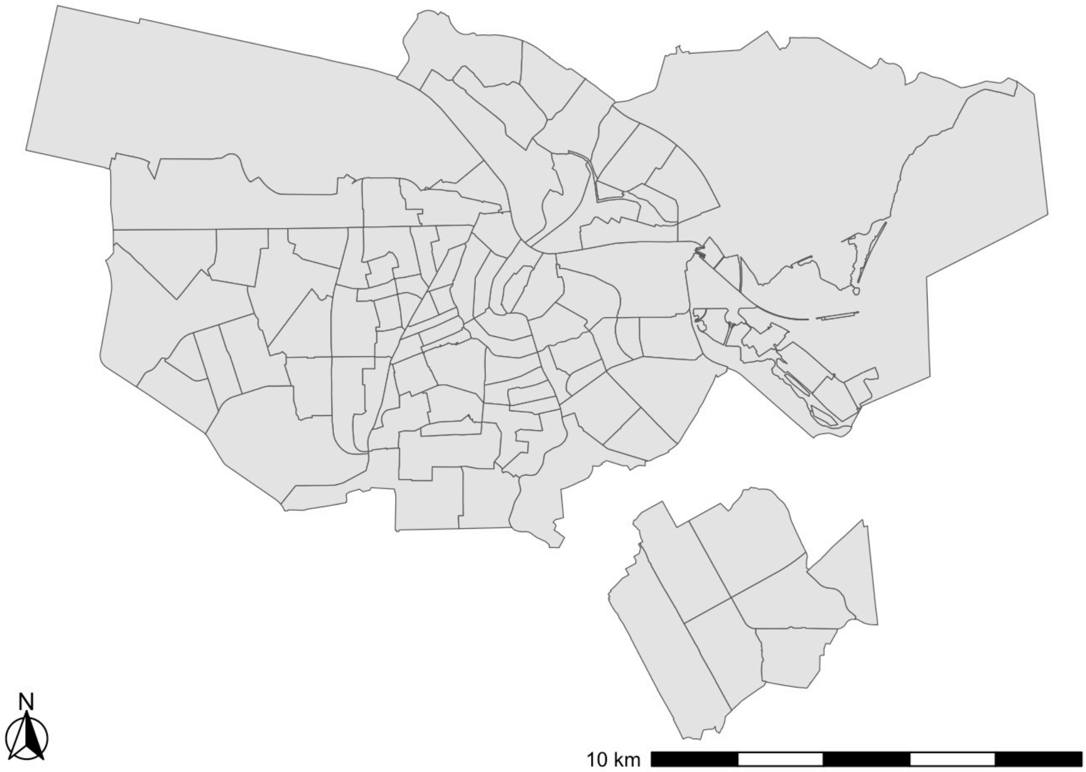
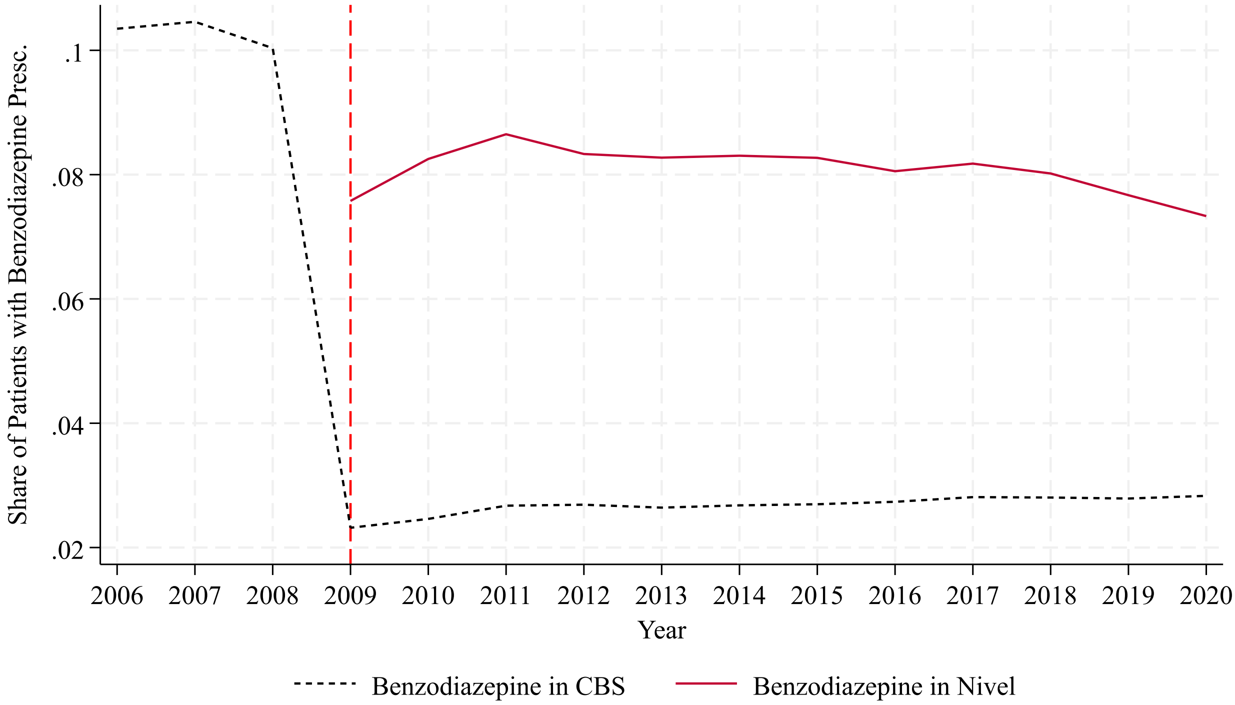
A Appendix

Figure A.1: Amsterdam neighborhoods



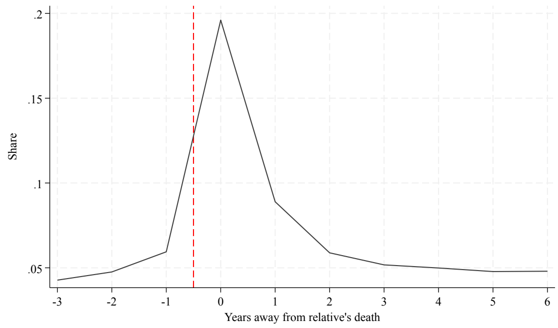
Notes: The figure shows a map of the city of Amsterdam into wijken (neighborhoods), the statical area classification used in this paper.

Figure A.2: Benzodiazepines prescriptions in Nivel and CBS over time

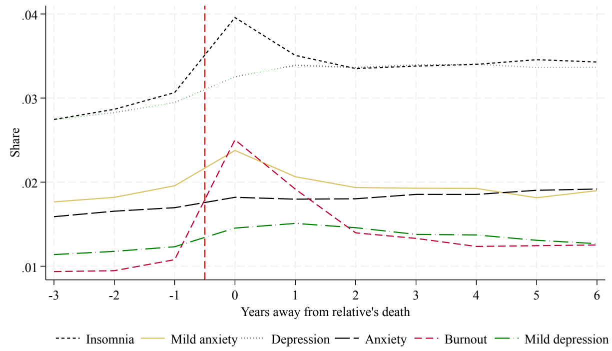


Notes: The figure shows the share of patients with any benzodiazepine prescriptions between 2006 and 2020. Source: Nivel and Statistics Netherlands microdata.

Figure A.3: Other diagnoses



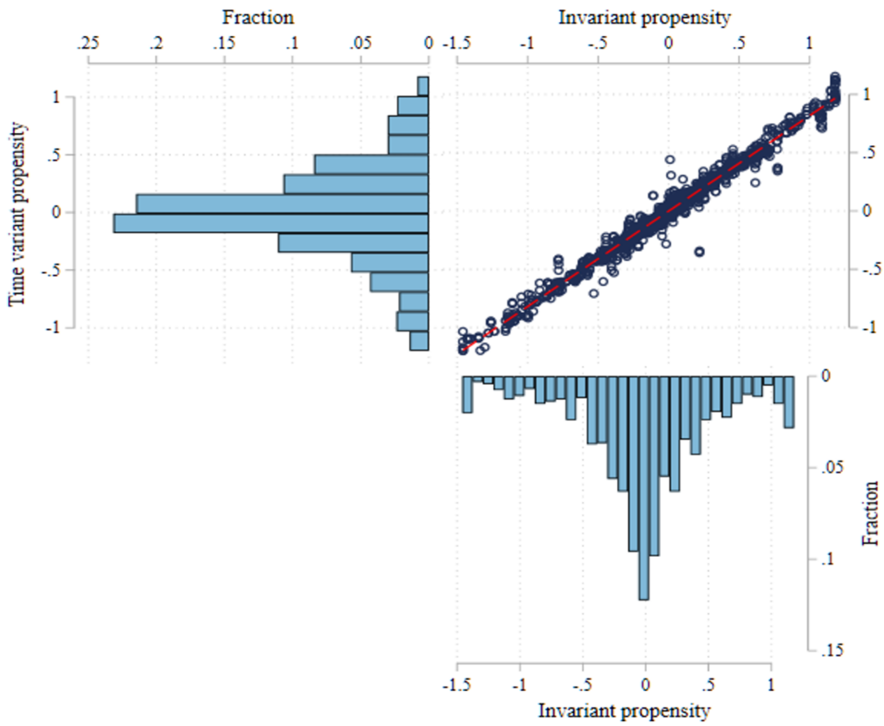
(a) Social problem diagnoses



(b) Psychological diagnoses

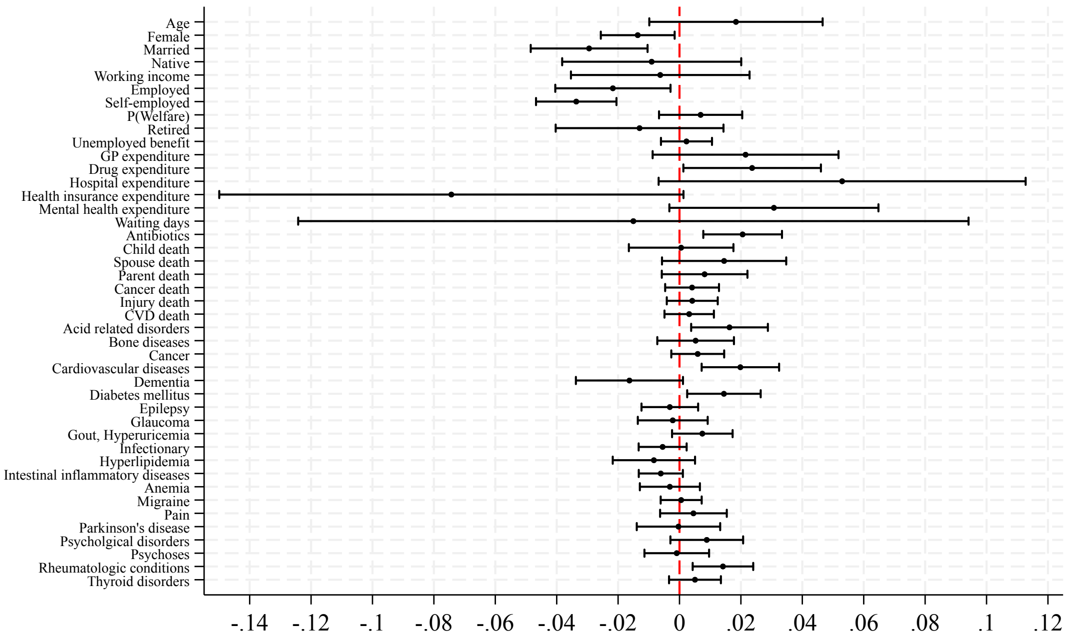
Notes: The figure shows the changes in social issue diagnosis and addiction-related diagnoses (panel (a)) and the breakdown of psychological diagnoses (panel (b)) around the relative death. The loss occurs between 2009 and 2019. N=288,587. Source: Nivel and Statistics Netherlands microdata.

Figure A.4: Time-varying vs. time-invariant propensity to prescribe benzodiazepines



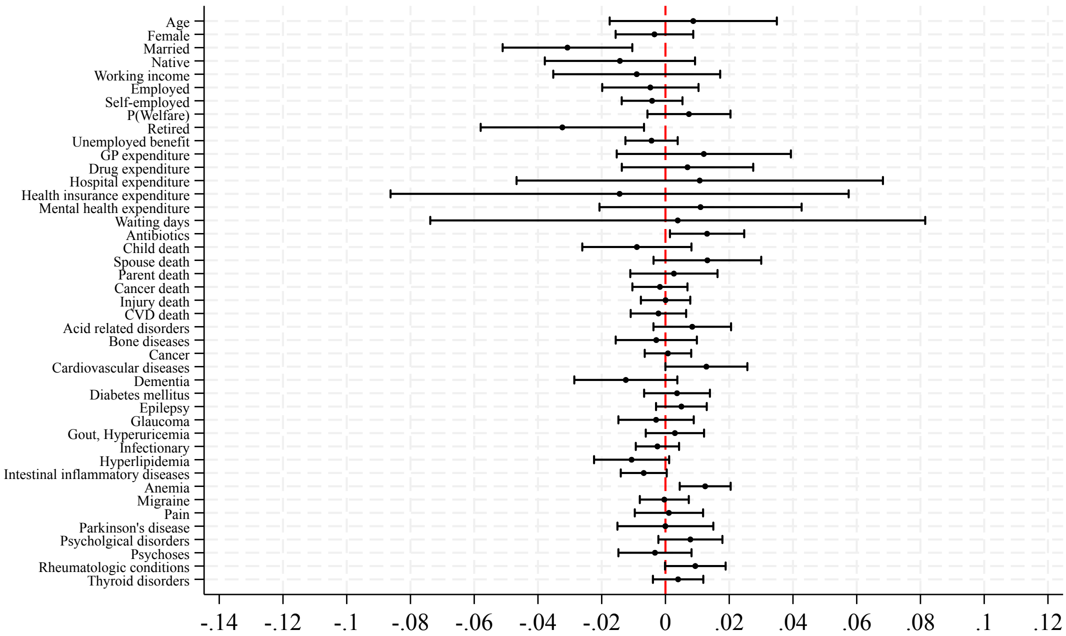
Notes: The figure shows the distribution and the correlation (scatterplot) between the time-invariant propensity (x-axis) and the time-varying propensity (y-axis) to prescribe benzodiazepines. The time-varying version is based on a 3-year period calculation (2009–2011, 2012–2014, 2015–2017, 2018–2020). The coefficient of correlation is 0.85. N = 534 practices. Source: Nivel and Statistics Netherlands microdata.

Figure A.5: Balancing test: unconditional propensity to prescribe benzodiazepine



Notes: *This figure tests for random assignment of GP to patients in our working sample using the unconditional propensity to prescribe (share of patients with a benzodiazepine prescription on the total number of patients of a practice). The F-test statistic is 2.67 and the p-value is 0.000. All regressors are standardized. Regression coefficients and their accompanying 95% confidence intervals are plotted. N = 74,391. Robust standard errors are clustered at the GP level. Source: authors' calculations using Nivel and Statistics Netherlands.*

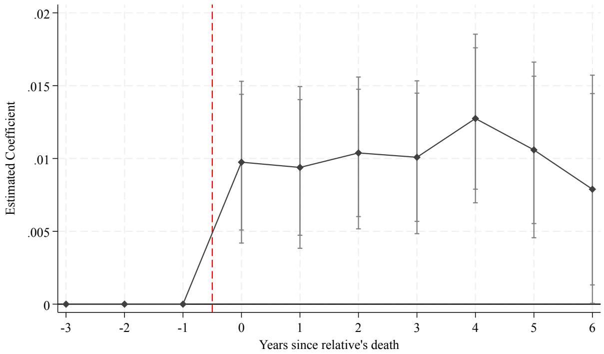
Figure A.6: Balancing test: propensity to prescribe benzodiazepine conditional on neighborhood fixed effect (no demographic characteristics)



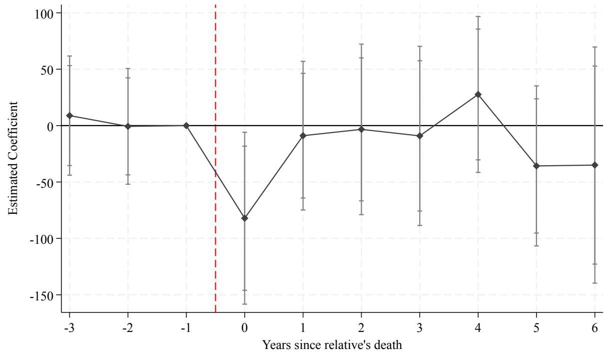
Notes: This figure tests for random assignment of GP to patients in our working sample using a modified version of our propensity to prescribe benzodiazepines that only accounts for geographical differences (the term γ_w in Equation (2)). In particular, we regress the modified GP propensity on all observables jointly (patient demographics and previous medical history). The F-test statistic is 1.495 and the p-value is 0.026. All regressors are standardized. Regression coefficients and their accompanying 95% confidence intervals are plotted. $N = 74{,}391$. Robust standard errors are clustered at the GP level. Source: authors' calculations using Nivel and Statistics Netherlands.

Figure A.7: Main estimates excluding cancer

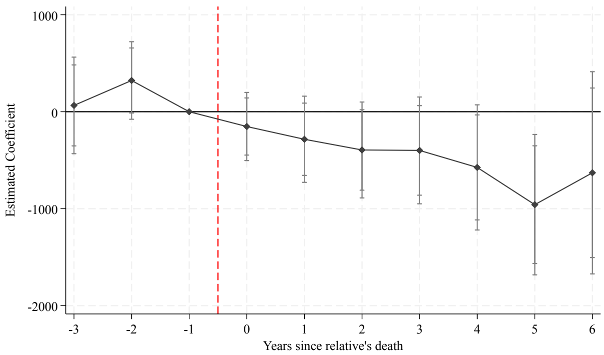
(a) Benzodiazepine prescriptions



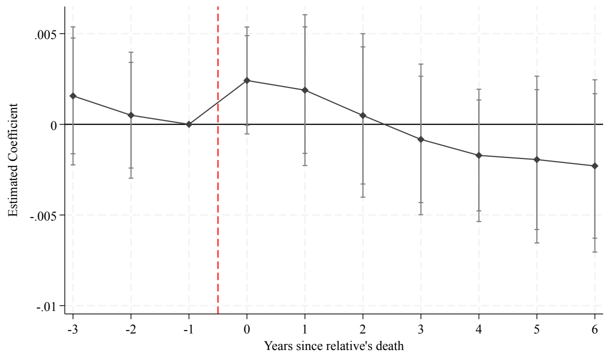
(b) Mental health care expenditure



(c) Income from work



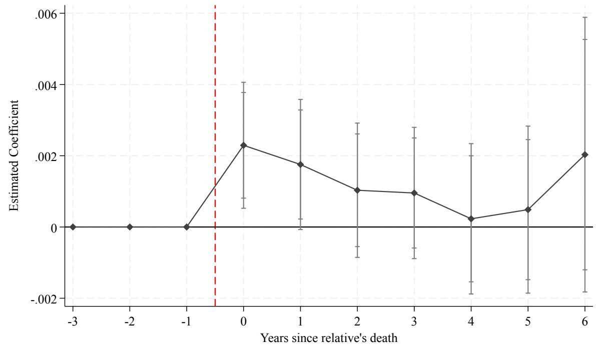
(d) Probability of unemployment benefits



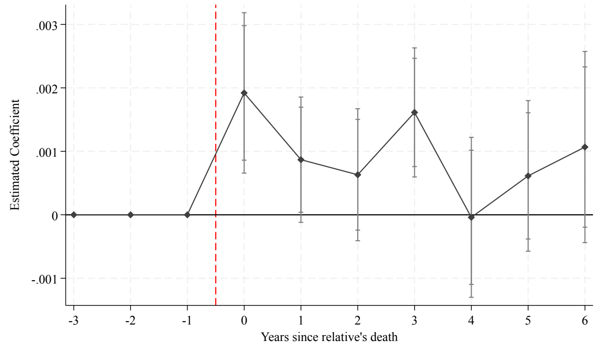
Notes: For each event time, the figure displays the estimate of the γ_k coefficients reported in Equation 3 excluding from the analysis relative deaths for cancer. We show the result for the following outcomes: a) the probability of receiving a benzodiazepine prescription ($N = 362,273$), b) Mental health care expenditure ($N = 438,325$), c) Income from work ($N = 461,005$) and probability of unemployment benefits ($N = 464,285$). We report 90% and 95% level confidence intervals (standard errors clustered at the practice level). Source: authors' calculations using Nivel and Statistics Netherlands microdata.

Figure A.8: Breakdown of Red-flag treatments

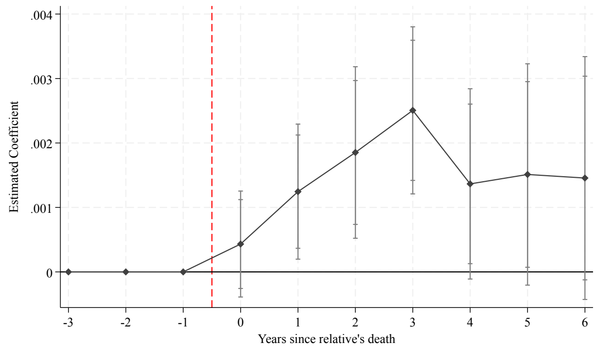
(a) RF1: 1st prescription and no justifying diagnosis



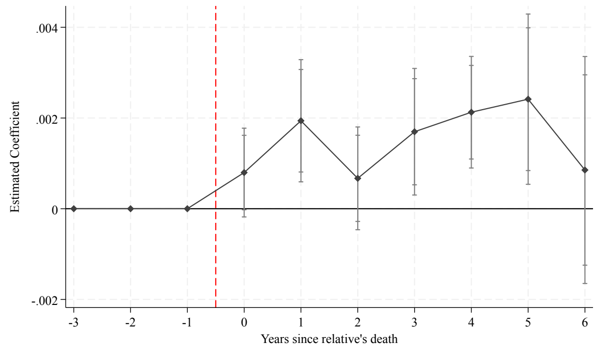
(b) RF2: 1st prescription and only diagnosed with feeling anxious/nervous/tense



(c) RF3: prolonged prescriptions



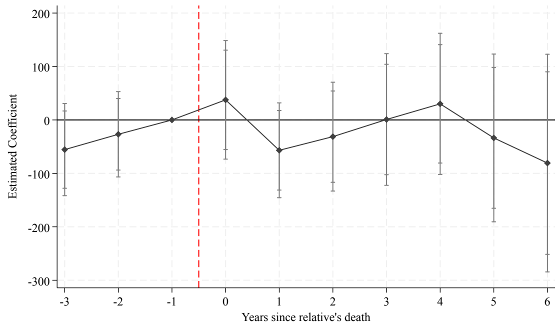
(d) RF4: benzodiazepine and opioids in the same month



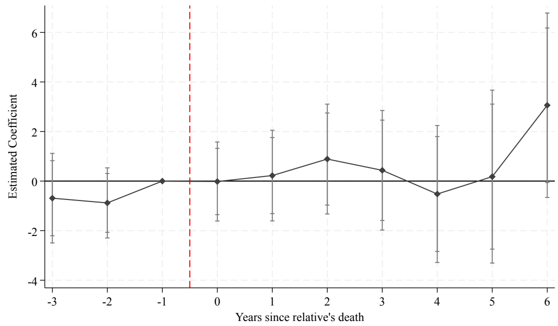
Notes: For each event time, the figure displays the estimate of the γ_k coefficients reported in Equation 3, namely the estimated difference in the probability of receiving one of the four red-flag treatments (as described in Section 3) resulting from a one-unit increase in the propensity to prescribe benzodiazepines. We report 90% and 95% level confidence intervals (standard errors clustered at the practice level). N =580,840 patient-years. Source: authors' calculations using Nivel and Statistics Netherlands microdata.

Figure A.9: Health care expenditure breakdown

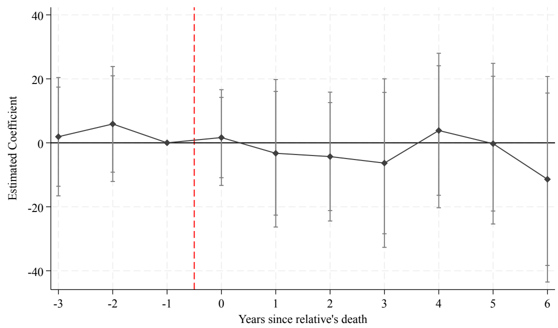
(a) Total health expenditure excluding mental health



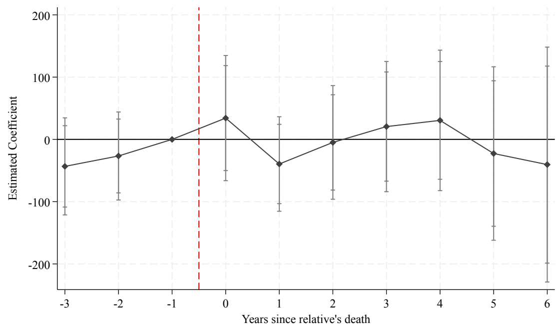
(b) GP Expenditure



(c) Drugs Expenditure



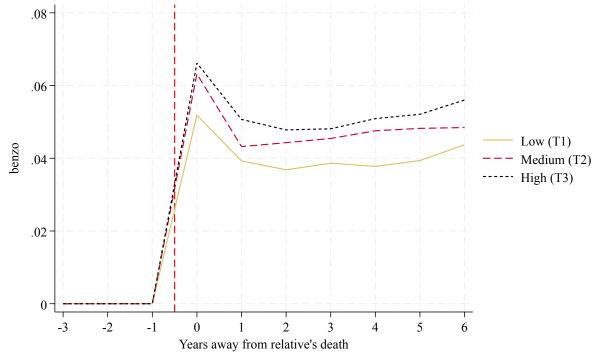
(d) Hospital Expenditure



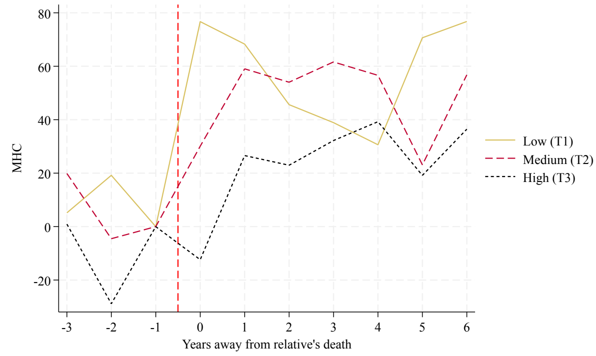
Notes: *For each event time, the figure displays the estimate of the γ_k coefficients reported in Equation 3, namely the estimated difference in expenditures for (a) Non-mental health care expenditures (N =674,165), (b) GP care expenditure (N =704,257), (c) Drug expenditure (N =704,257), or (d) Hospital expenditures (N =704,257), resulting from a one unit increase in the propensity to prescribe benzodiazepines. We report 90% and 95% level confidence intervals (standard errors clustered at the practice level). Source: authors' calculations using Nivel and Statistics Netherlands microdata.*

Figure A.10: Raw trends by tercile of the propensity to prescribe benzodiazepine

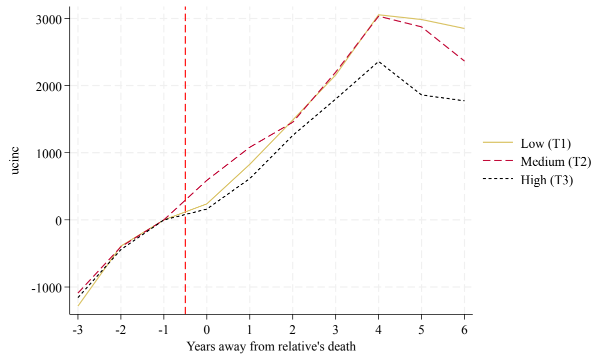
(a) Benzodiazepine prescriptions



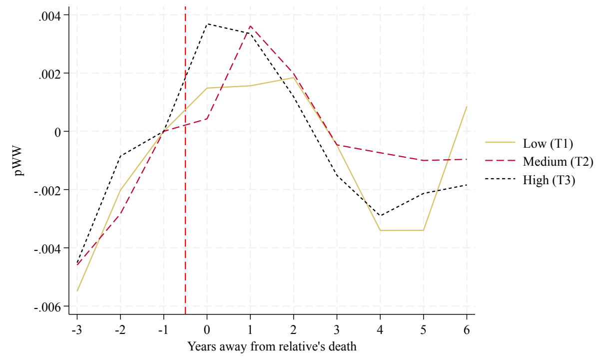
(b) Mental health care expenditure



(c) Income from work

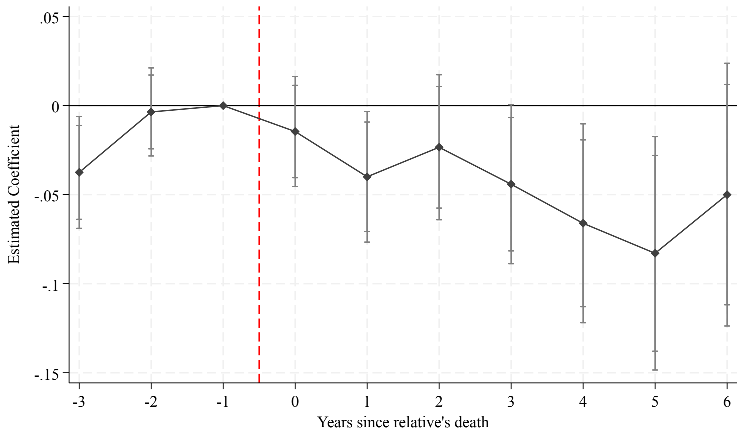


(d) Probability of unemployment benefits



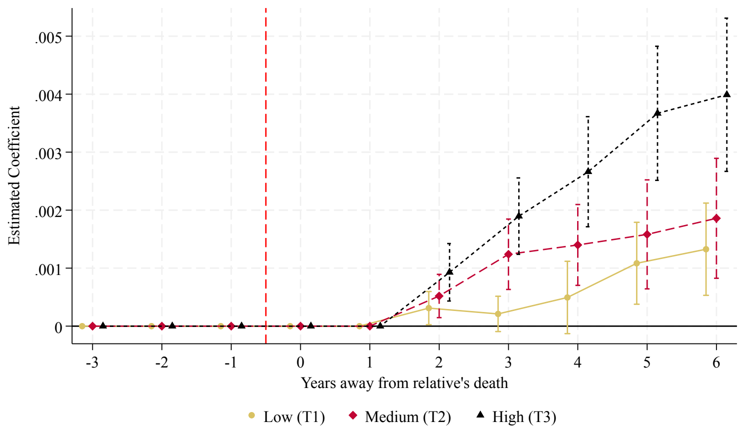
Notes: For each event time and outcome, the figure displays the raw means by tercile of the propensity to prescribe a benzodiazepine around the death of a close relative. We show the following outcomes: a) benzodiazepine prescriptions ($N = 580,840$), b) Mental health care expenditure ($N = 704,257$), c) Income from work (N =740,588), and d) probability of unemployment benefits (N =746,069). Source: authors' calculations using Nivel and Statistics Netherlands microdata.

Figure A.11: Log income



Notes: For each event time, the figure displays the estimate of the γ_k coefficients reported in Equation 3, namely the estimated difference in log income resulting from a one unit increase in the propensity to prescribe benzodiazepines ($N = 740{,}588$). We report 90% and 95% level confidence intervals (standard errors clustered at the practice level). Source: authors' calculations using Nivel and Statistics Netherlands microdata.

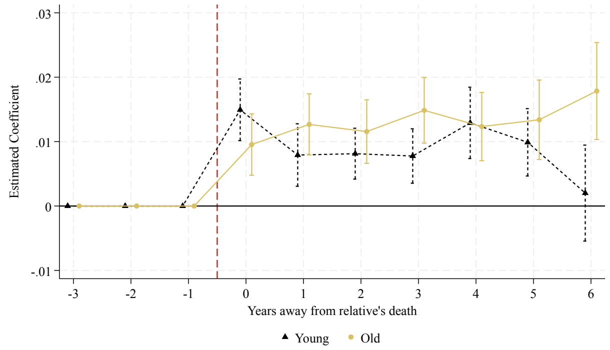
Figure A.12: Six prescriptions per year for three consecutive years



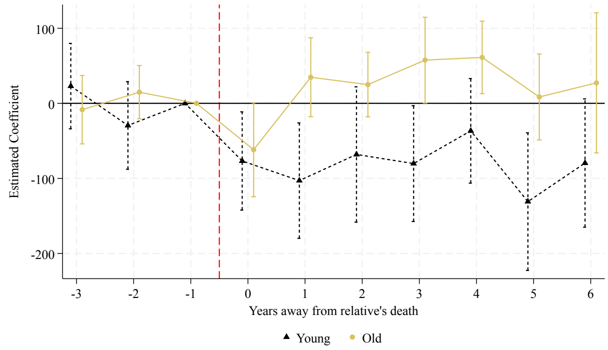
Notes: For each event time, the figure displays the estimate of the event study coefficients (δ_k coefficients reported in Equation 3 without interaction terms) by tercile of the propensity to prescribe benzodiazepines. We show the results for the probability of having six prescriptions per year for three consecutive years (N =580,840). We report 90% and 95% level confidence intervals (standard errors clustered at the practice level). Source: authors' calculations using Nivel and Statistics Netherlands microdata.

Figure A.13: Heterogeneity by age: effect on main outcomes

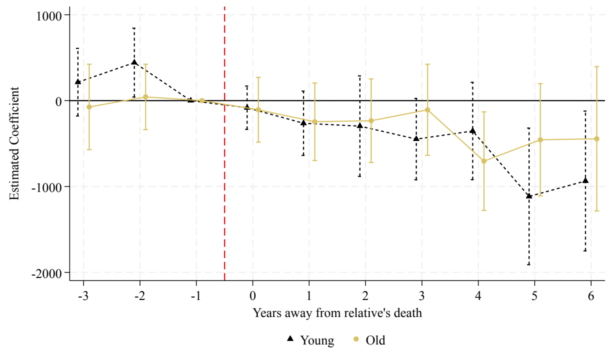
(a) Benzodiazepine prescriptions



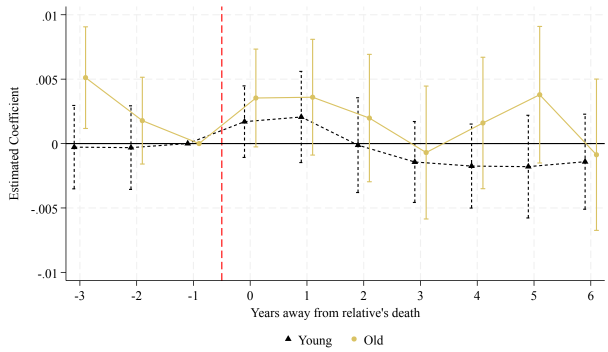
(b) Mental health care expenditure



(c) Income from work



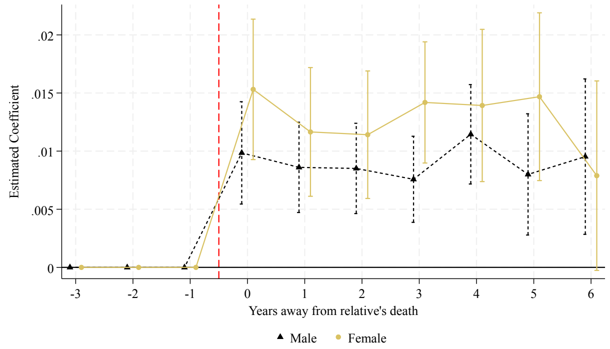
(d) Probability of unemployment benefits



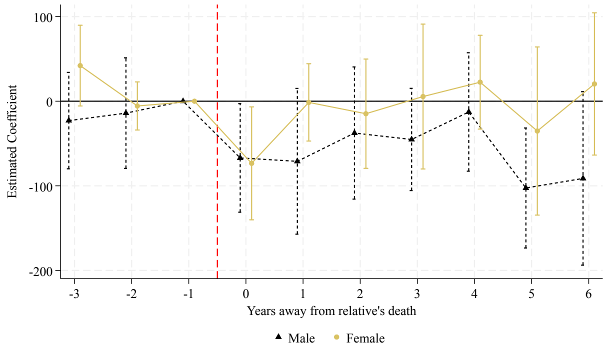
Notes: The figure displays the heterogeneity in our main results running separated regression by age groups (below and above 45 years old). Specifically, for each event time and age group the figure displays the estimate of the γ_k coefficients reported in Equation 3, namely the estimated difference in following outcomes: (a) probability of receiving a benzodiazepine prescription ($N_y = 318,855$; $N_o = 261,985$), (b) Mental health care expenditure ($N_y = 390,369$; $N_o = 313,888$), (c) Income ($N_y = 409,487$; $N_o = 331,101$), or (d) Probability of unemployment benefits ($N_y = 413,297$; $N_o = 332,772$). We report 90% and 95% level confidence intervals (standard errors clustered at the practice level). Source: authors' calculations using Nivel and Statistics Netherlands microdata.

Figure A.14: Heterogeneity by sex: effect on main outcomes

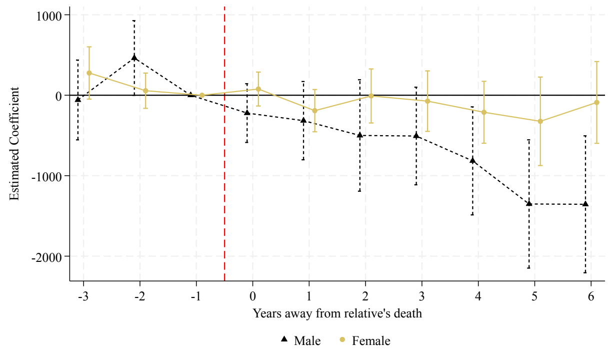
(a) Benzodiazepine prescriptions



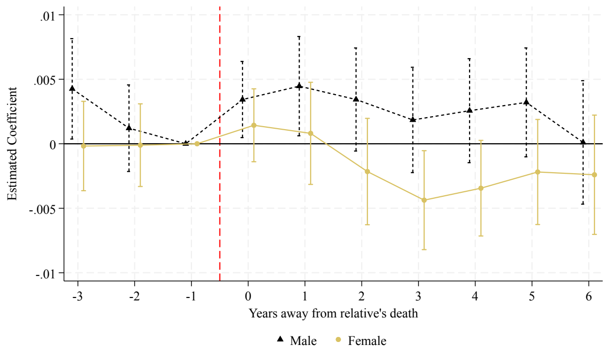
(b) Mental health care expenditure



(c) Income from work

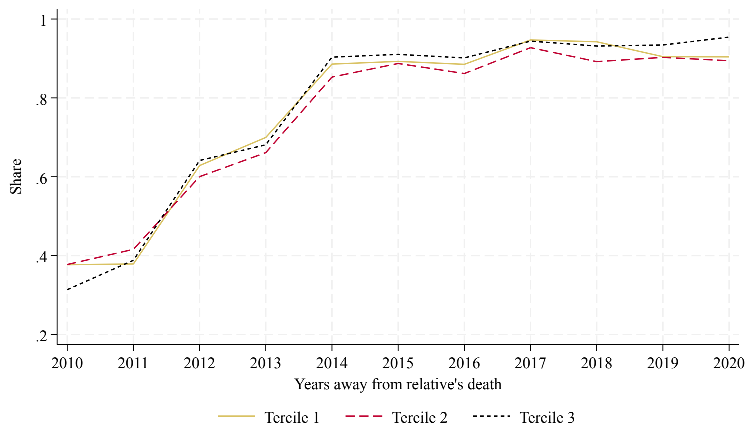


(d) Probability of unemployment benefits



Notes: The figure displays the heterogeneity in our main results running separated regression by gender. Specifically, for each event time and age group the figure displays the estimate of the γ_k coefficients reported in Equation 3, namely the estimated difference in the following outcomes: (a) benzodiazepine prescriptions ($N_m = 304,585$; $N_f = 276,255$), (b) Mental health care expenditure ($N_m = 369,251$; $N_f = 335,006$), (c) Income ($N_m = 387,781$; $N_f = 352,807$), or (d) Probability of unemployment benefits ($N_m = 391,262$; $N_f = 354,807$). We report 90% and 95% level confidence intervals (standard errors clustered at the practice level). Source: authors' calculations using Nivel and Statistics Netherlands microdata.

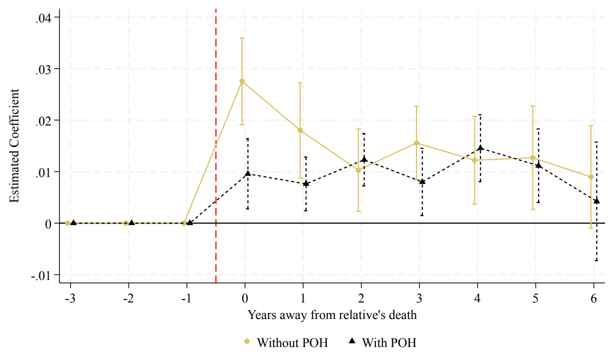
Figure A.15: Rollout of mental health nurses into Dutch GP practices



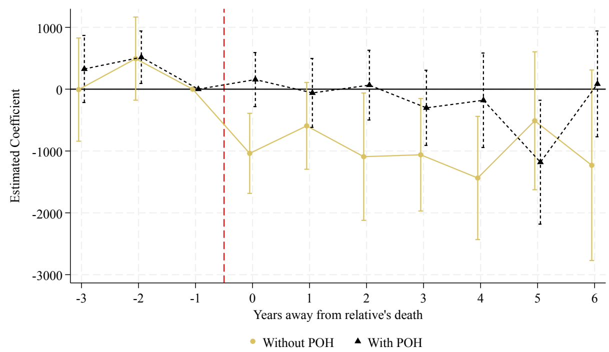
Notes: The figure shows the share of GP practices with any mental health nurse by terciles of the propensity to prescribe benzodiazepines between 2010 and 2020. Number of GP practices = 534. Number of observations (practice X year)=3,908. Source: authors' calculations using Nivel and Statistics Netherlands microdata.

Figure A.16: Effects on benzodiazepine prescription and income by POH with time restriction

(a) Benzodiazepine prescriptions



(b) Income from work

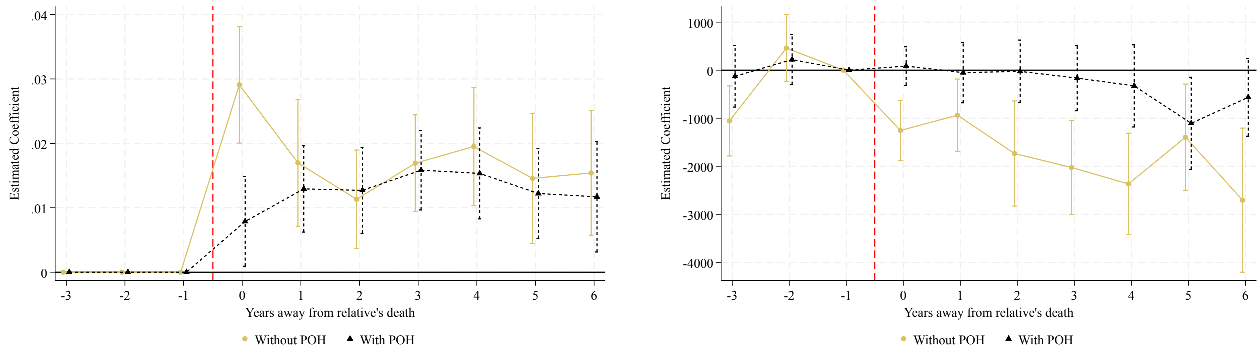


Notes: For each event time, this figure shows the estimated γ_k coefficients from Equation 3. Specifically, it illustrates the estimated difference in (a) benzodiazepine prescription ($N = 298{,}185$) (b) income from work ($N = 374{,}698$) resulting from a one-unit increase in the propensity to prescribe benzodiazepines for patients experiencing bereavement within three years before or after the nurse is hired. We report 90% and 95% level confidence intervals (standard errors clustered at the practice level). Source: authors' calculations using Nivel and Statistics Netherlands microdata.

Figure A.17: Effects on benzodiazepine prescription and income by POH with cohort restriction

(a) Benzodiazepine prescriptions

(b) Income from work

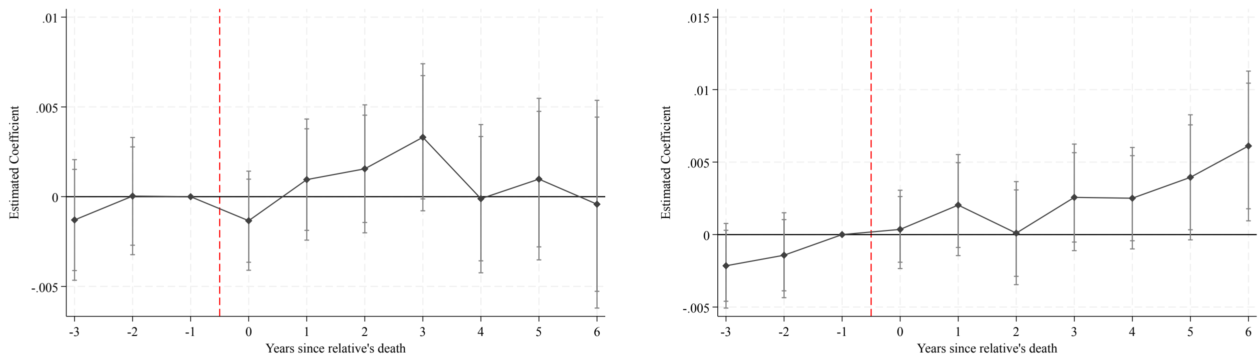


Notes: *For each event time, this figure shows the estimated γ_k coefficients from Equation 3. Specifically, it illustrates the estimated difference in (a) benzodiazepine prescription (N = 247,415) (b) income from work (N = 313,568) resulting from a one-unit increase in the propensity to prescribe benzodiazepines for cohorts 2011–2013. We report 90% and 95% level confidence intervals (standard errors clustered at the practice level). Source: authors' calculations using Nivel and Statistics Netherlands microdata.*

Figure A.18: Probability of being prescribed antidepressants and opioids

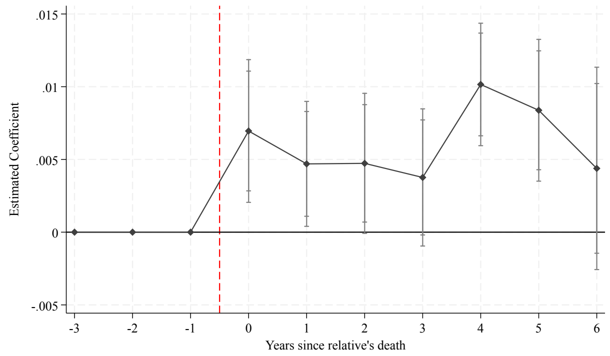
(a) Antidepressants

(b) Opioids

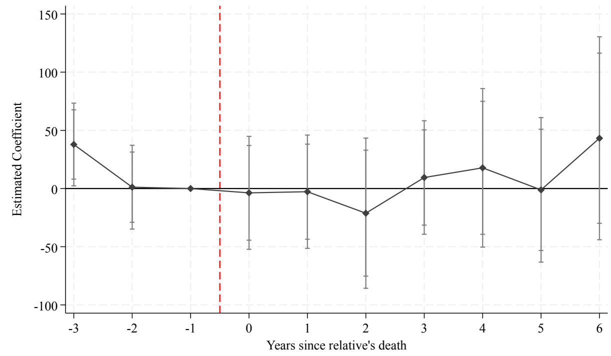


Notes: *For each event time, the Figure displays the estimate of the γ_k coefficients reported in Equation 3, namely the estimated difference in the probability of receiving (a) a prescription of antidepressants (N06A), and (b) a prescription of opioids (N02A), resulting from a one unit increase in the propensity to prescribe benzodiazepines. We report 90% and 95% level confidence intervals (standard errors clustered at the practice level). N =580,844 patient-years. Source: authors' calculations using Nivel and Statistics Netherlands microdata.*

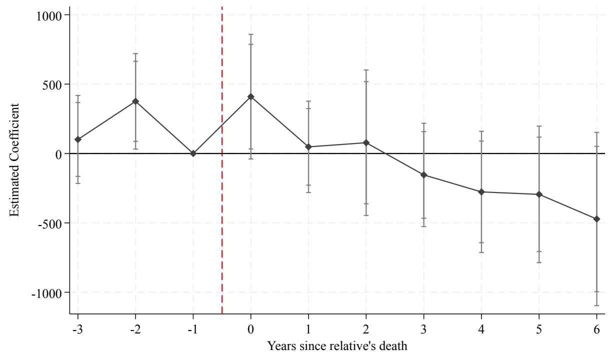
Figure A.19: Propensity to prescribe antibiotics: effect on main outcomes



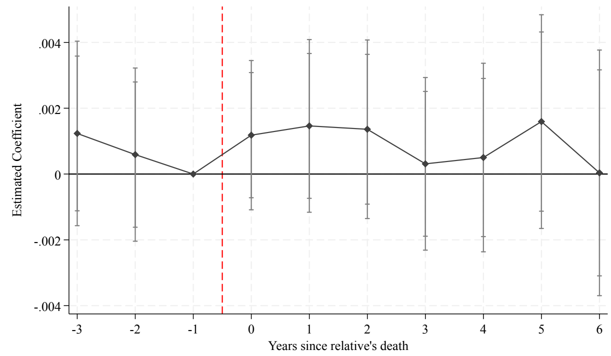
(a) Benzodiazepine prescriptions



(b) Mental health care expenditure



(c) Income

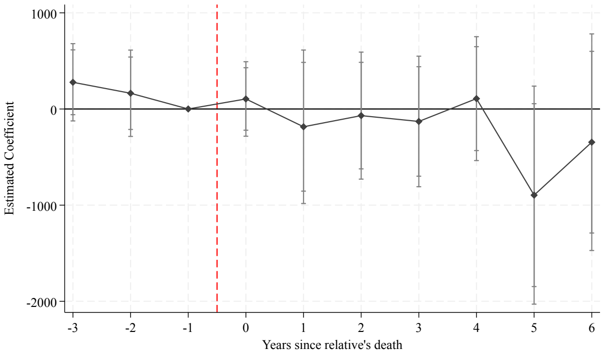


(d) Probability of unemployment benefits

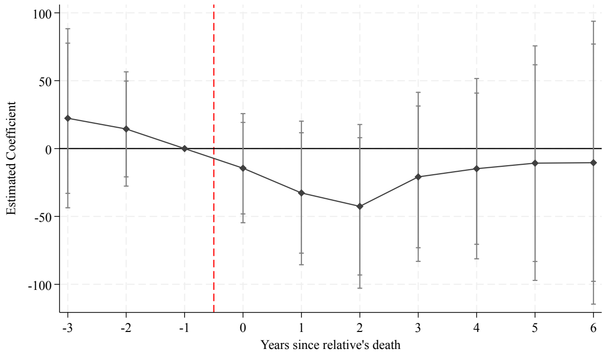
Notes: For each event time, the Figure displays differences in (a) the probability of receiving a benzodiazepine prescription ($N = 580,840$), (b) Mental health care expenditure ($N = 704,257$), (c) Income from work (N =740,588), or (d) Probability of unemployment benefits (N =746,069), resulting from a one unit increase in the propensity to prescribe antibiotics calculated as in Equation 3 but using probability of receiving an antibiotic prescription as outcome variable. We report 90% and 95% level confidence intervals (standard errors clustered at the practice level). Source: authors' calculations using Nivel and Statistics Netherlands microdata.

Figure A.20: Effects on wealth

(a) Wealth from investments



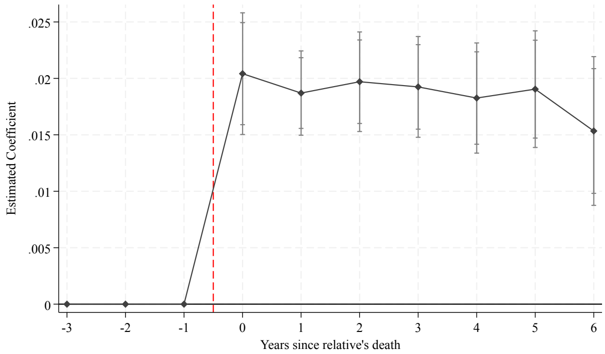
(b) Wealth from estate



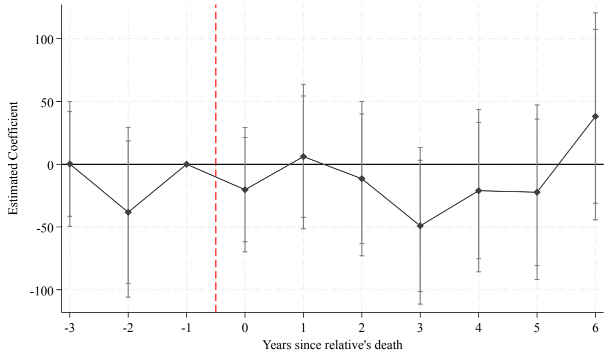
Notes: *For each event time, this figure shows the estimated γ_k coefficients from Equation 3. Specifically, it illustrates the estimated difference in (a) wealth from investments ($N = 662{,}068$) (b) wealth from estate ($N = 662{,}068$) resulting from a one-unit increase in the propensity to prescribe benzodiazepines for patients experiencing bereavement within three years before or after the nurse is hired. We report 90% and 95% level confidence intervals (standard errors clustered at the practice level). Source: authors' calculations using Nivel and Statistics Netherlands microdata.*

Figure A.21: Propensity to prescribe benzodiazepine with practice FE: effect on main outcomes

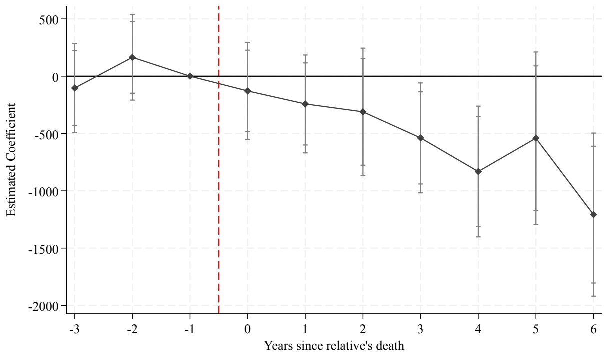
(a) Benzodiazepine prescriptions



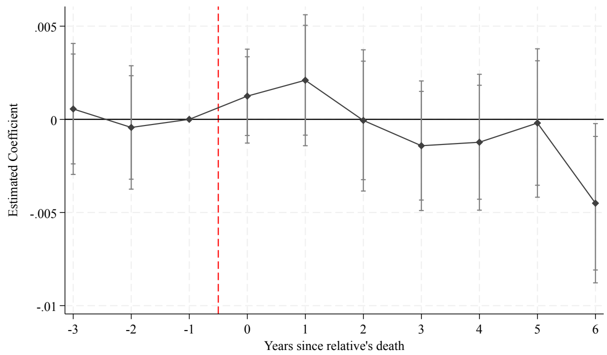
(b) Mental health care expenditure



(c) Income



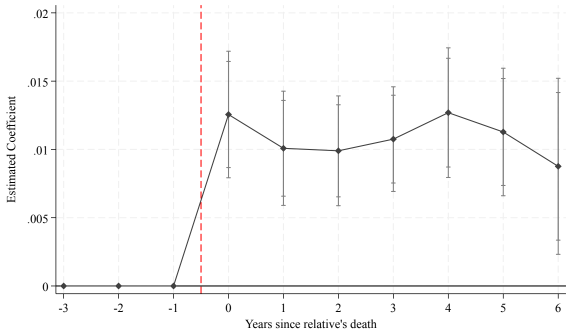
(d) Probability of unemployment benefits



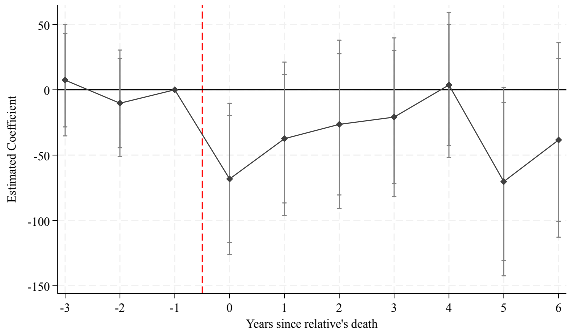
Notes: For each event time, the figure displays differences in expenditures for (a) benzodiazepine prescriptions ($N = 580,840$), (b) Mental health care expenditure ($N = 704,257$), (c) Income, or (d) Probability of unemployment benefits (N =746,069), resulting from a one unit increase in the propensity to prescribe benzodiazepine calculated using the alternative propensity to prescribe benzodiazepine described in Equation (4). We report 90% and 95% level confidence intervals (standard errors clustered at the practice level). Source: authors' calculations using Nivel and Statistics Netherlands microdata.

Figure A.22: Effects on main outcomes excluding patients living more than 10 km away from GP practice

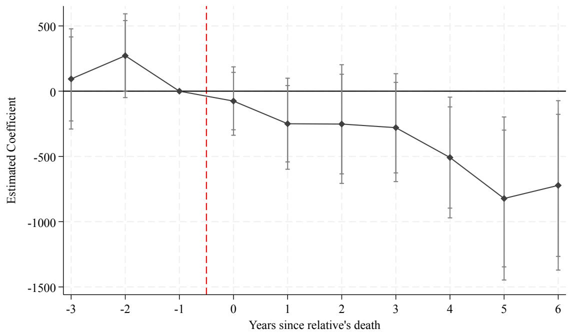
(a) Benzodiazepine prescriptions



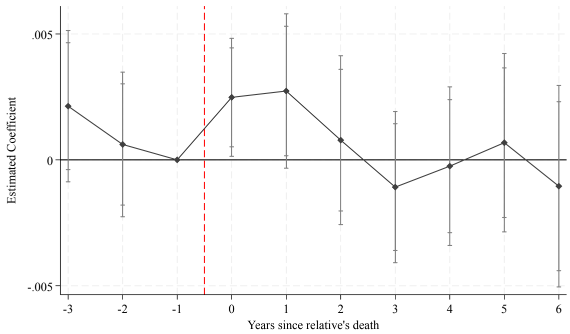
(b) Mental health care expenditure



(c) Income



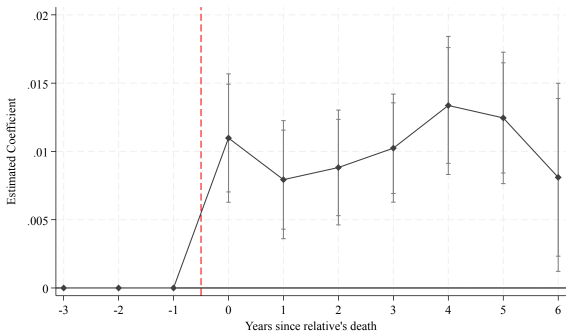
(d) Unemployment benefits



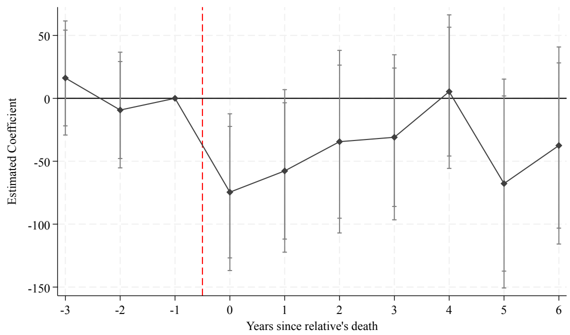
Notes: For each event time, the figure displays the estimate of the γ_k coefficients reported in Equation 3 excluding from the analysis relative patients living more than 10 km away from the GP practice. We show the result for the following outcomes: a) benzodiazepine prescriptions (N = 580,719), b) Mental health care expenditure (N = 704,067), c) Income (N = 740,409) and probability of unemployment benefits (N = 745,868). We report 90% and 95% level confidence intervals (standard errors clustered at the practice level). Source: authors' calculations using Nivel and Statistics Netherlands microdata.

Figure A.23: Main estimates using only parents' death

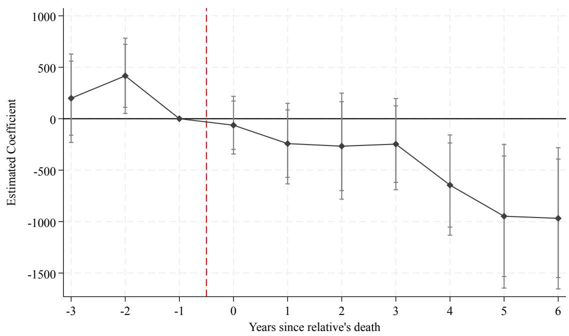
(a) Benzodiazepine prescriptions



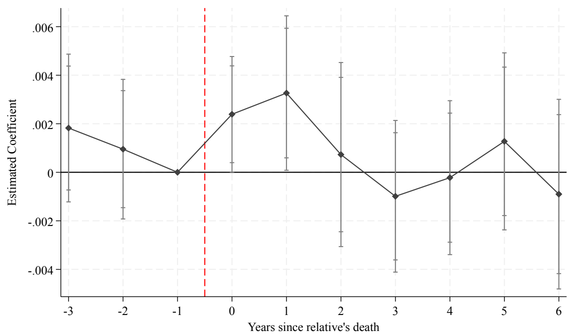
(b) Mental health care expenditure



(c) Income



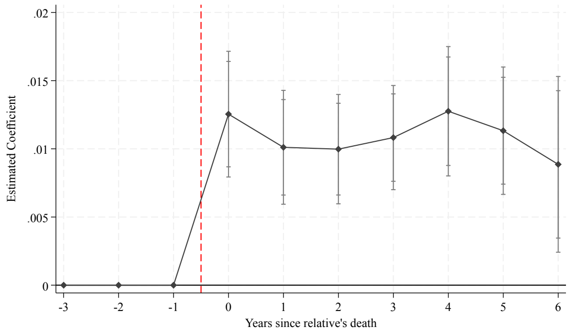
(d) Unemployment benefits



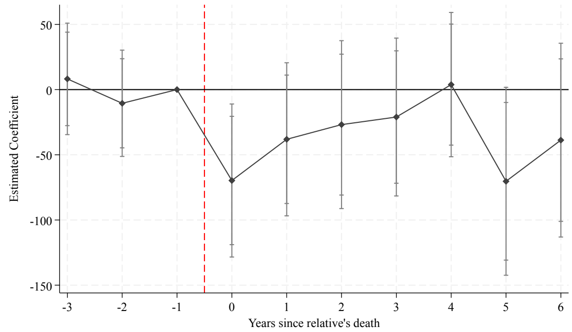
Notes: the figure displays the estimate of the γ_k coefficients reported in Equation 3 using only parents as relative death (i.e., excluding spouse, siblings, and children). We show the result for the following outcomes: a) the probability of receiving a benzodiazepine prescription ($N = 504{,}456$); b) Mental health care expenditure ($N = 611{,}444$); c) Income from work ($N = 643{,}348$) and d) probability of unemployment benefits ($N = 648{,}083$). We report 90% and 95% level confidence intervals (standard errors clustered at the practice level). Source: authors' calculations using Nivel and Statistics Netherlands microdata.

Figure A.24: Main estimates accounting for relative death heterogeneity

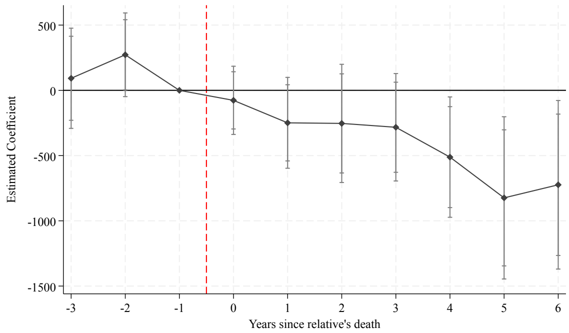
(a) Benzodiazepine prescriptions



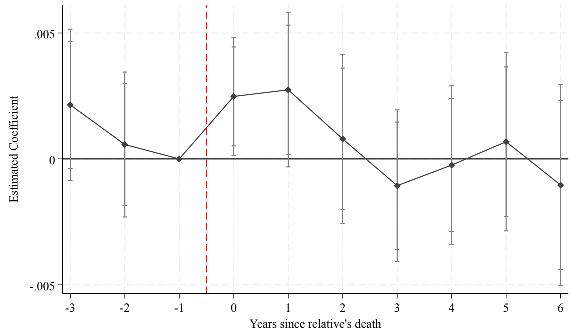
(b) Mental health care expenditure



(c) Income



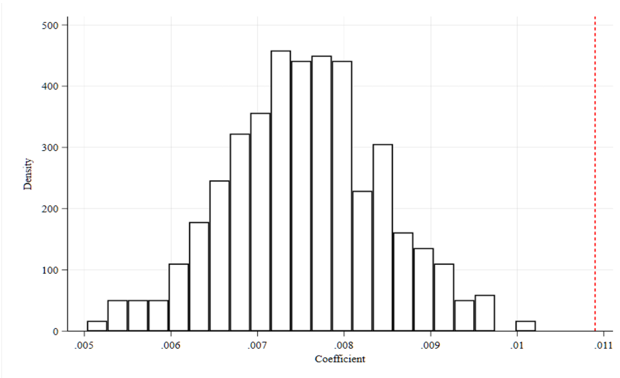
(d) Unemployment benefits



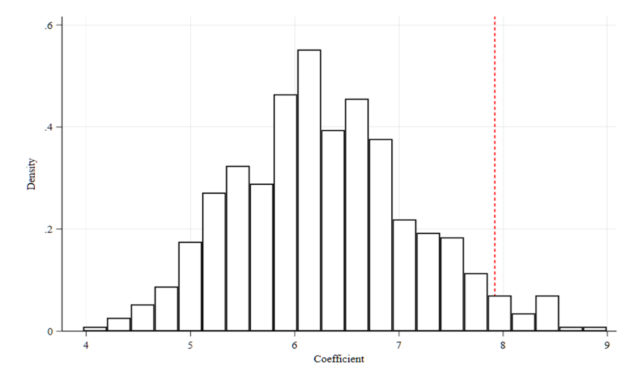
Notes: The figure displays the estimate of the γ_k coefficients, reported in Equation (3), augmenting the estimated model with a full set of interaction between relative death type dummies (children, spouse, and siblings), and event time dummies. We show the result for the following outcomes: a) benzodiazepine prescriptions ($N = 580,840$); b) Mental health care expenditure ($N = 704,257$); c) Income ($N = 740,588$); d) probability of unemployment benefits ($N = 746,069$). We report 90% and 95% level confidence intervals (standard errors clustered at the practice level). Source: authors' calculations using Nivel and Statistics Netherlands microdata.

Figure A.25: Permutation test

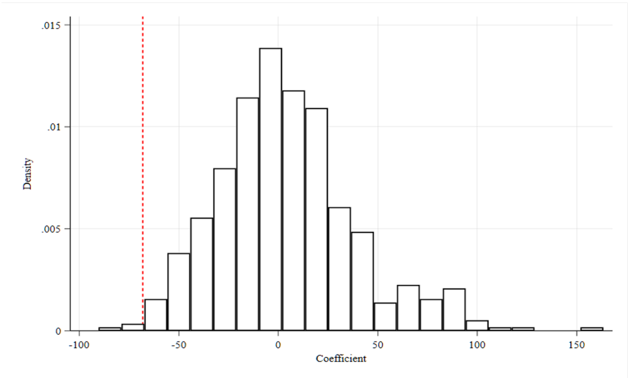
(a) Benzodiazepine: coefficients, Percentile=1



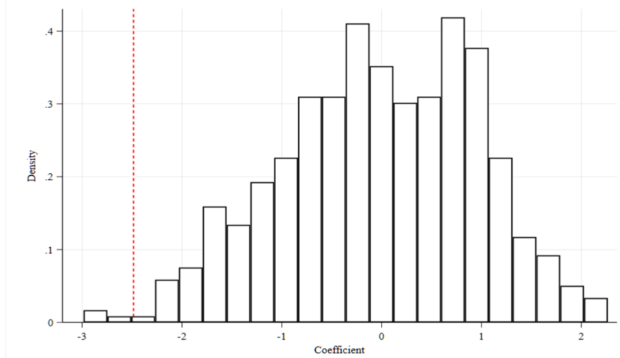
(b) Benzodiazepine: t-statistic, Percentile=96.4



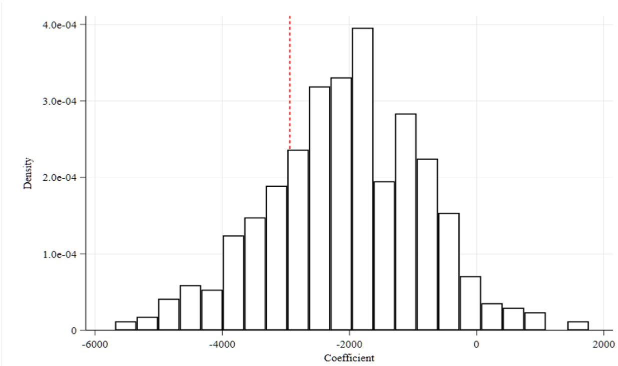
(c) Mental Health care: coefficients, Percentile=0.006



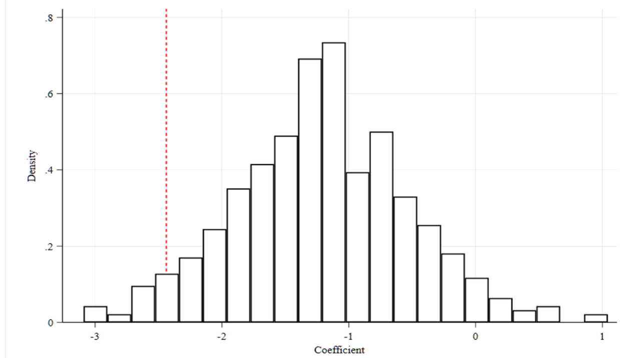
(d) Mental Health care: t-statistic, Percentile=0.006



(e) Income from work: coefficients, Percentile=0.222



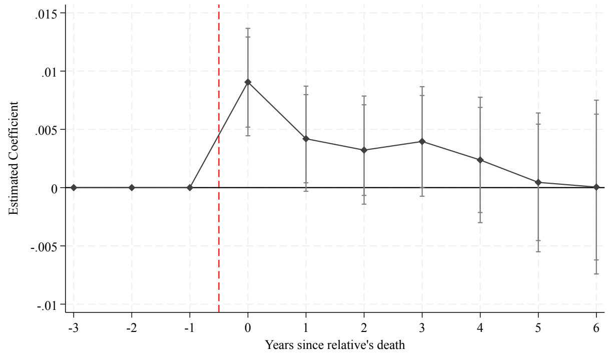
(f) Income from work: t-statistic, Percentile=0.038



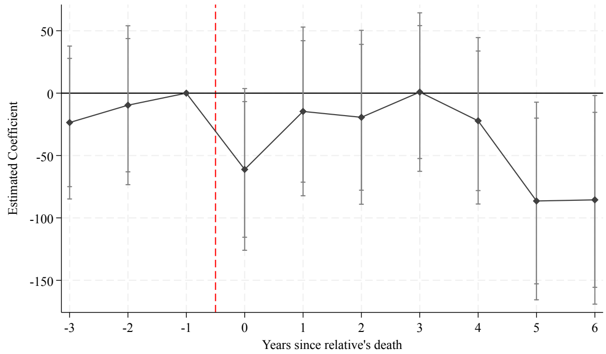
Notes: Each panel displays the distribution of the estimated γ_k coefficients (left column) or the corresponding t-statistics (right column) from Equation (3) under 500 random permutations of a placebo death in a random sample of 100'000 patients in the Nivel GP data in the same age range as those in our working sample. Panels refer to three outcomes: (1) benzodiazepine prescriptions, (2) mental health care expenditure, and (3) work income. The position of the red dashed line illustrates how the main event-study estimate compares to the null distribution implied by random shocks. Source: Authors' calculations based on Nivel and Statistics Netherlands microdata.

Figure A.26: Main estimates without washout period

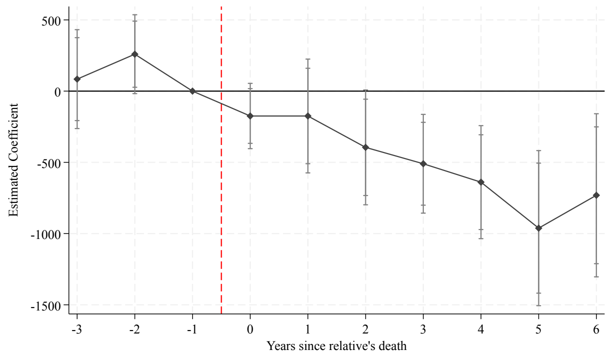
(a) Benzodiazepine prescriptions



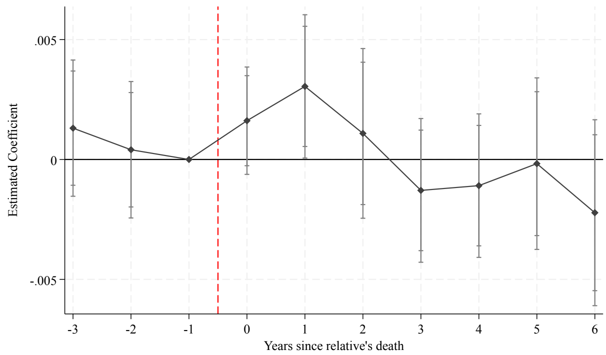
(b) Mental health care expenditure



(c) Income from work



(d) Probability of unemployment benefits



Notes: For each event time, the figure displays the estimate of the γ_k coefficients reported in Equation 3 without using the 4-year washout period on benzodiazepine and mental health diagnoses. We show the result for the following outcomes: a) probability of receiving a benzodiazepine prescription (N = 703,781), b) Mental health care expenditure (N = 847,374), c) Income (N = 892,363), and d) probability of unemployment benefits (N =898,908). We report 90% and 95% level confidence intervals (standard errors clustered at the practice level). Source: authors' calculations using Nivel and Statistics Netherlands microdata.

Table A.1: Dutch full population (CBS) vs Nivel Sample

	CBS	Nivel	Standardized differences
Age	47.64	45.41	0.09
Female	0.5	0.51	-0.02
Non-migrant backgound	0.78	0.79	-0.01
Income	26785	27518	-0.01
Employed	0.67	0.71	-0.05
Self-employed	0.07	0.07	0.00
Recipient social assistance	0.11	0.11	-0.01
Retired	0.2	0.16	0.07
Recipient unemployment benefits	0.02	0.02	0.00
GP expenses	153.23	153.91	0.00
Drugs expenses	300.35	259.45	0.02
Hospital expenses	1,342	1,072	0.03
Mental health expenses	253.89	310.82	-0.01
Total health expenses	2,296	2,015	0.03
Any therapy	0.05	0.05	-0.02
Medicine use in the year			
Antibiotics	0.22	0.21	0.03
Acid related disorders	0.28	0.26	0.03
Bone diseases	0.03	0.02	0.02
Cancer	0.01	0.01	0.00
Cardiovascular diseases	0.46	0.43	0.06
Diabetes mellitus	0.11	0.1	0.03
Epilepsy	0.05	0.05	0.01
Glaucoma	0.03	0.02	0.01
Gout, Hyperuricemia	0.02	0.02	0.02
Infectionary	0.02	0.02	0.00
Hyperlipidemia	0.28	0.26	0.03
Intestinal inflammatory diseases	0.01	0.01	0.00
Anemia	0.03	0.03	0.01
Migraines	0.04	0.04	-0.01
Pain	0.13	0.12	0.02
Parkinson’s disease	0.07	0.07	0.01
Psycholgical Disorders	0.15	0.16	-0.01
Psychoses	0.04	0.04	-0.01
Rheumatologic conditions	0.38	0.39	-0.02
Thyroid disorders	0.07	0.07	0
N	14,568,340	2,318,227	

Note: The Table displays the sample’s means for the listed characteristics between patients in the full Dutch population (based on CBS) and in the subsample of patients with GP data (based on Nivel) for the year 2015. The third column reports the standardized differences, calculated to test the difference across the two samples. Source: authors’ calculations using Nivel and Statistics Netherlands microdata.

Table A.2: Sample selection summary

Description	Sample Size
Full Nivel Sample	2,658,652
People with a Relative Death	137,569
Sample Restriction:	
— Washout period	111,567
— Age 18-60 at the Time of the Loss	76,407

Note: The table summarizes the sample selection process and shows how the sample size is progressively reduced based on the inclusion criteria. The initial full Nivel sample includes all individuals with available records. The "People with a Relative Death" criterion selects those who experienced the loss of a close relative (and are observed also in the year before). The "Washout period" restriction excludes individuals with prior mental health treatments or diagnoses within up to four years before the event (number of years conditional on data availability). Finally, the age restriction ensures that the sample is limited to individuals aged 18-60 at the time of the loss.

Table A.3: Working sample: Descriptive Statistics

Variable	Mean	Standard Deviation
Age	46.44	9.419
Female	0.476	0.499
Married	0.621	0.485
Non-migrant background	0.899	0.313
Working income	40,761	40,350
Employed	0.874	0.332
Self-employed	0.089	0.284
Social Assistance	0.094	0.292
Retired	0.012	0.107
Unemployed	0.022	0.145
GP expenditure	130.09	81.325
Drug expenditure	216.08	1478.40
Hospital expenditure	883.06	4887.42
Mental health expenditure	148.35	2646.03
Total health expenditure	1541.94	6166.82
Regional waiting times for specialized mental health care (days)	64.2	8.79
Deceased relative		
Child	0.012	0.11
Spouse	0.031	0.174
Parent	0.868	0.338
Sibling	0.088	0.284
Cause of relative's death		
Cancer	0.377	0.485
Cardiovascular disease	0.253	0.435
Injury	0.009	0.097
Medicine use in the year		
Antibiotics	0.186	0.389
Acid related disorders	0.093	0.291
Bone diseases	0.006	0.076
Cancer	0.003	0.055
Cardiovascular diseases	0.142	0.349
Diabetes mellitus	0.031	0.173
Epilepsy	0.015	0.12
Glaucoma	0.005	0.073
Gout, Hyperuricemia	0.007	0.084
Infectionary	0.005	0.071
Hyperlipidemia	0.071	0.257
Intestinal inflammatory diseases	0.006	0.075
Anemia	0.01	0.098
Migraine	0.022	0.145
Pain	0.039	0.194
Parkinson's disease	0.007	0.083
Psycholgical disorders	0.043	0.202
Psychoses	0.01	0.097
Rheumatologic conditions	0.188	0.39
Thyroid disorders	0.025	0.156

Note: The Table displays the sample's means for the final working sample used to estimate Equation (3) in the year before the relative death (event time -1). Source: authors' calculations using Nivel and Statistics Netherlands microdata.

Table A.4: Balancing table: Mean differences in patients' observable characteristics at t-1: first vs. third tercile of the propensity distribution

	Tercile 1	Tercile 3	Standardized Differences
Age	46.44	46.3	0.01
Female	0.47	0.48	0.00
Married	0.61	0.61	0.01
Non-migrant background	0.89	0.88	0.02
Income	41,388.11	40,056.90	0.02
Employed	0.87	0.87	0.02
Self-employed	0.09	0.09	0.01
Recipient social assistance	0.09	0.9	0.01
Retired	0.01	0.01	0.01
Recipient unemployment benefits	0.02	0.02	0.00
GP expenses	126.8	130.91	-0.04
Drugs expenses	195.16	222.92	-0.01
Hospital expenses	828.66	934.06	-0.01
Mental health expenses	111.04	111.55	0.00
Total health expenses	1,414.98	1,565.97	-0.02
Regional waiting times for specialized mental health care (days)	65.39	64.21	0.09
Deceased relative			
Child	0.01	0.01	0.00
Spouse	0.03	0.03	-0.01
Parent	0.87	0.87	0.01
Sibling	0.09	0.09	0
Cause of relative's death			
Cancer	0.38	0.38	-0.01
Cardiovascular disease	0.25	0.25	0.01
Injury or accident	0.01	0.01	0.00
Medicine use in the year			
Antibiotics	0.17	0.19	-0.04
Acid related disorders	0.22	0.23	-0,03
Bone diseases	0.01	0,01	0.00
Cancer	0.01	0.01	0.00
Cardiovascular diseases	0.35	0.35	0.00
Diabetes mellitus	0.08	0.08	0.00
Epilepsy	0.03	0.03	-0.01
Glaucoma	0.01	0.01	0.01
Gout, Hyperuricemia	0.02	0.02	0.01
Infectionary	0.01	0.01	0.01
Hyperlipidemia	0.18	0.17	0.01
Intestinal inflammatory diseases	0.01	0.01	0.02
Anemia	0.02	0.02	-0.02
Migraines	0.05	0.05	0.00
Pain	0.1	0.1	-0.01
Parkinson's disease	0.01	0.01	-0.01
Psycholgical disorders	0.10	0.10	0.00
Psychoses	0.02	0.02	0.00
Rheumatologic conditions	0.46	0.47	-0.01
Thyroid disorders	0.06	0.06	0.00
N	24,455	24,520	

Note: The Table displays the sample's means for the listed characteristics one year before the death of the relative between patients treated by practices in the 1st and 3rd tercile of the estimated propensity to prescribe benzodiazepine. The third column reports the standardized differences, calculated to test the difference between the two groups. Source: authors' calculations using Nivel and Statistics Netherlands microdata.

Table A.5: Correlation with waiting times

	Event time 0	Event time -1	Pre-period
	(1)	(2)	(3)
pp_i^j	-0.00071 (0.00120)	-0.00049 (0.00145)	-0.0007 (0.00169)
N	611,451	504,541	612,888

Notes: The table displays the correlation between our estimated propensity to prescribe at the individual level and the waiting times of her municipality at the time of the loss (time 0) in the year before (-1) and the average waiting time in the pre-period.

Table A.6: Survival Analysis: Probability of death

Weibull	Log-normal	Log-logistic	Exponential	Gamma
0.031	-0.023	-0.018	0.031	-0.018
(0.069)	(0.044)	(0.04)	(0.069)	(0.04)

Notes: The table displays the estimated difference in death probability (after the death of a close relative) resulting from a one-unit increase in the propensity to prescribe benzodiazepines using parametric survival regressions under 5 different distributional assumptions (Weibull, Log-normal, Log-logistic, Exponential and Gamma distribution). Standard errors are clustered at the practice level. Significance levels: *** $p < .01$, ** $.01 \leq p < .05$, * $.05 \leq p < .10$. *Source: authors' calculations using Nivel and Statistics Netherlands microdata.*