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End-of-Life Medical Spending: Patterns and Household Spillovers

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Abstract

Medical spending is highly concentrated at the end of life and varies widely across patients, raising a first-order welfare question about whether marginal end-of-life spending reflects waste or generates meaningful benefits. Using Austrian administrative data, we document that endof-life spending has grown markedly over time and remains highly dispersed even conditional on diagnosis, with predicted mortality explaining only a small share of the variation. We then study a largely underexplored margin: spillovers onto surviving spouses. Event study estimates show large and persistent changes in spouses' employment and healthcare use around spousal death. However, these dynamics are essentially invariant to the decedent's end-of-life spending intensity, a finding that is robust to different measures of spending intensity and to an instrumental variables design exploiting provider-level practice variation. Together, these results are consistent with an important role for inefficiencies in end-of-life care

JEL classification

I10, I11, I12, I14, I18, J12

Keywords

end-of-life, healthcare expenditure, efficiency, health shock, labor supply

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1. Introduction

Medical spending is highly concentrated at the end of life (Zeltzer et al., 2023), making end-of-life care a central component of aggregate healthcare spending and a natural focal point for debates over what drives healthcare costs. End-of-life spending also varies tremendously across patients. This heterogeneity in treatment intensity, which has been documented even conditional on the medical diagnosis, raises a first-order welfare question: does the marginal dollar spent near the end of life reflect waste and overuse of medical services, or does it generate meaningful benefits valued by patients and families? In this paper, we first characterize end-of-life spending in Austria—its level, trend, and cross-patient variation—and then move beyond the decedent to a largely understudied margin by asking whether higher end-of-life spending spills over onto the outcomes of surviving spouses.

Because our analysis conditions on death, it does not speak to whether marginal end-of-life spending actually prolongs life. However, even conditional on death and its cause, differences in end-of-life spending can plausibly generate spillovers onto surviving spouses by shifting the time, stress, and financial burdens borne by the household during the terminal phase of life. Higher spending may substitute for informal caregiving, reducing the need for spouses to cut hours or leave work. But it can also raise time costs through care coordination, responding to frequent admissions and short-notice medical events, and making repeated trips to the hospital, potentially reducing work hours and job attachment. These labor market effects may be amplified by financial pressure: end-of-life care can tighten household liquidity through out-of-pocket costs and contemporaneous earnings or wealth losses, inducing additional labor supply responses even absent any effects on survival. Spending may also affect spouses' health by raising (or reducing) stress and uncertainty and intensifying the psychological burden of end-of-life decisions. Finally, greater exposure to the healthcare system during the terminal phase may mechanically shift survivors' own healthcare utilization by lowering the fixed costs of accessing care and increasing diagnosis and treatment of previously unmet needs.

We use high-quality Austrian administrative healthcare claims data covering the universe of private sector workers, unemployed individuals, and retirees with private sector employment histories, along with their dependents, and link these records to additional administrative registers, in particular longitudinal labor market information from the Austrian Social Security Database (ASSD, Zweimüller et al., 2009). We begin by documenting patterns and trends in end-of-life spending, both over time and across patients. We then study surviving spouses. We first estimate dynamics in labor market outcomes and healthcare spending around spousal death conditional on a rich set of age and diagnosis fixed effects using event studies. Next, we construct a measure of excess end-of-life spending by benchmarking each decedent's terminal spending to a counterfactual of non-terminal care—that is, the spending we would expect absent imminent death given diagnosis and baseline risk—defined as expected annual spending among patients who survive at least as long as the decedent, share the same diagnosis, and have similar predicted mortality risk at diagnosis. Finally, we interact the event study design with this excess spending measure to test whether higher end-of-life spending alters survivors' labor market and health trajectories around the time of death.

We find that end-of-life spending is quantitatively important in Austria. Although only about one percent of the population dies each year, spending in the last year of life accounts for more than ten percent of aggregate medical spending. End-of-life spending rises sharply over time, increasing from about 17,000 € per decedent in 2006 to about 28,000 € in 2018, which corresponds to roughly four percent annual growth. At the individual level, spending is highly dispersed and only weakly related to predicted mortality at diagnosis. As in Zeltzer et al. (2023), we find that even after conditioning on diagnosis and predicted mortality, spending is substantially higher for decedents than for observationally similar survivors. Reweighting survivor spending to match the mortality-risk profile of decedents reduces the spending gap between decedents and survivors only slightly, implying that differences in baseline prognosis explain little of the excess spending on those who die. Nearly all of the remaining gap is accounted for by variation in inpatient care. End-of-life spending also varies systematically by socioeconomic status: more advantaged patients, such as the college educated, have lower predicted mortality risk at diagnosis yet exhibit a larger decedent-survivor spending gap, consistent with more intensive hospital-based care conditional on prognosis.

Turning to household spillovers, we document sizeable changes in survivors' labor market and health trajectories around spousal death, including declines in employment and pronounced increases in mental healthcare use that persist well after the spouse's death. However, these responses are essentially invariant to the decedent's excess end-of-life spending. Interacted event studies show no systematic differences in survivors' labor market behavior, healthcare utilization, or mental health across the excess spending distribution, and the same conclusion holds when we separate inpatient, outpatient, and drug spending. These findings are robust to alternative constructions of excess spending and to an instrumental variables design that exploits plausibly exogenous provider-level variation in excess spending. Taken together, the results suggest that while spousal death has large and persistent effects on survivors, marginal differences in end-of-life spending do not appear to meaningfully attenuate or amplify these consequences. From a welfare perspective, the absence of detectable survivor benefits suggests that cross-patient variation in end-of-life spending is unlikely to be justified by improvements in dependents' economic or health outcomes. More broadly, the results are consistent with substantial dispersion driven by low-value and potentially wasteful end-of-life care.

Our contribution to the literature is threefold. First, we add to the growing literature on the dynamics and variation of medical spending at the end of life. A large body of research shows that the final year of life accounts for a disproportionate share of total healthcare expenditure, ranging from eight to eleven percent across OECD countries (French et al., 2017) and up to one quarter of Medicare spending in the United States (Aldridge and Kelley, 2015; Emanuel and Emanuel, 1994; Riley and Lubitz, 2010). Most studies focus on cancer, documenting steep increases in medical costs during the final months of life due to frequent hospitalizations, intensive treatment, and costly life-sustaining interventions (Cheung et al., 2015; Earle et al., 2004; Margolis et al., 2017). Similar patterns are observed for other chronic and severe illnesses, although the timing, intensity, and composition of care differ somewhat across conditions (Leniz et al., 2021; Ng et al., 2025; Quinn et al., 2021; Reeve et al., 2018; Unroe et al., 2011; Vestergaard et al., 2023). Evidence from Austria points in the same direction: Robausch et al. (2021) document that end-of-life cancer care remains predominantly hospital-based with limited early integration of palliative services, while Breyer et al. (2022) show that disproportionate expenditure growth among cancer decedents is largely driven by rising costs per case associated with medical innovation.

Building on this work, we extend the focus to major terminal illnesses, providing new, population-wide evidence on how end-of-life spending in Austria has evolved over time and how it is distributed across patients. Moving beyond descriptive analyses, we examine the mechanisms that help explain why medical spending in the last year of life remains persistently high among terminally ill individuals. Following the framework of Zeltzer et al. (2023), we link predicted mortality to subsequent medical expenditures to disentangle variation driven by underlying health from that associated with treatment intensity. In doing so, we also explore the role of hospital-based maintenance care and systematic differences in spending across socioeconomic groups.

Second, we extend the analysis from patients to their families. A large body of research shows that illness or disability within a household affects the labor supply, income, and wellbeing of other family members, with caregiving demands, financial pressures, and the structure of social protection shaping these responses (Böckerman et al., 2025; Charles, 1999; Coile, 2004; Fadlon and Nielsen, 2019; García-Gómez et al., 2013; Hollenbeak et al., 2011; Jeon and Pohl, 2017; Kambourova and Hassink, 2019; Kim et al., 2018; Macchioni Giaquinto et al., 2022; Shen et al., 2019). A growing related literature examines the effects of fatal health events and documents that the death of a spouse can lead to substantial and often persistent adjustments in economic behavior and health. For example, Fadlon and Nielsen (2019, 2021) show increases in labor supply, particularly in households that face a large loss of income, together with increases in own health investments. Likewise, Böckerman et al. (2025) find that women and secondary earners increase their labor supply after a spouse's death, and that this adjustment is accompanied by substantial and persistent mental health deterioration. Consistent with this evidence, several studies emphasize the central role of survivor benefits in cushioning the loss of disposable income and reducing the need for self-insurance through continued employment (Böheim and Topf, 2020; Fadlon et al., 2019; Giupponi, 2019; Rabaté and Tréguier, 2024; van der Vaart et al., 2020).

We bridge these two strands of literature by focusing on the last year of life, following spouses' labor market and health responses from the final phase of illness into bereavement. Specifically, we trace changes in labor market attachment, healthcare use, and health status during the final year, when caregiving demands and emotional strain are greatest, and in the period after death, when bereavement and income loss take effect. Examining these dynamics in the Austrian context, where social protection is strong and healthcare is universally accessible, allows us to provide a comprehensive view of how end-of-life events shape the wellbeing of surviving spouses in a setting with limited financial constraints.

Finally, we use this framework to assess the efficiency and welfare implications of end-of-life medical care. This shift from describing what drives high medical spending to evaluating what it delivers allows us to situate our findings within the broader debate on the efficiency of late-life treatment (Einav et al., 2018; Emanuel and Emanuel, 1994; Zeltzer et al., 2023; Zhang et al., 2023). Although much of the existing literature documents variation in treatment intensity, prior evidence shows that greater medical spending does not necessarily lead to better access or quality of care (Fisher et al., 2003*a*; Landrum et al., 2008; Teno et al., 2005; Wright et al., 2008; Zhang et al., 2023), longer survival (Landrum et al., 2008; Skinner et al., 2006), or higher patient satisfaction (Fisher et al., 2003*b*; Temel et al., 2010).

We contribute to this debate by examining whether higher end-of-life expenditures generate tangible benefits for those left behind. Specifically, we test whether greater spending mitigates or amplifies the adverse labor market and health effects experienced by surviving spouses around the time of death. In doing so, we provide new evidence on the indirect welfare effects of end-of-life medical care and offer a broader perspective on what constitutes value in healthcare.

2. Institutional setting

2.1. Healthcare and social security

Austria operates a universal social health insurance system with mandatory coverage financed primarily through payroll contributions shared between employers and employees, complemented by transfers from general tax revenues that are used largely for hospital financing. As of 2025, the statutory health insurance contribution rate is 7.65 percent, split between employers (3.87 percent) and employees (3.78 percent). Because health insurance is not tied to employment and enrollment is automatic, insurance coverage is essentially universal at 99.9 percent (Ahammer et al., 2021).

Healthcare provision is effectively two-tiered. Most care is delivered by public providers contracted with the social insurance system, alongside parallel private markets for outpatient services and selected specialized facilities. These private providers typically offer similar services and are used primarily to bypass waiting times rather than to access different treatments. Hospitals are financed through a DRG-type reimbursement system, while contracted outpatient providers are generally reimbursed on a fee-for-service basis. There is no formal gatekeeping requirement, although general practitioners are typically the first point of contact.

Cost-sharing is limited. Prescription drugs are subject to a fixed per-prescription fee (7.55 € as of 2025), and inpatient stays involve a daily copayment charged for up to 28 days per year (12.9 € in 2025). Supplementary private insurance is available but mainly upgrades amenities (for example, single rooms and physician choice) and covers private-physician expenses rather than expanding the core benefit package.

End-of-life treatment in Austria is predominantly hospital-based. Roughly half of all deaths occur in hospitals, implying that inpatient care accounts for a large share of terminal care (Stolz et al., 2020). Among cancer patients, a majority of decedents die during an inpatient stay, and hospital admissions are common in the final weeks of life (Robausch et al., 2021). This is consistent with Austria's large hospital sector in international comparison and its high supply of hospital beds relative to the OECD average (OECD, 2025).

2.2. The labor market

Austria's labor market combines strong industrial relations with relatively high flexibility. Wage setting and working conditions are shaped to a large extent by sectoral collective bargaining (Böheim, 2017). At the same time, job protection is comparatively weak and worker turnover is high relative to many other European countries (OECD, 2020).[1] Employment contracts can generally be terminated without stating a cause, though employer-initiated terminations must respect a minimum notice period of six weeks. Unemployment has historically been low, ranging from 4.72 in 1998 to 5.21 in 2018 (OECD, 2023). Female labor force participation remains comparatively low, and part-time work is widespread among women, with close to half of employed women working part-time.

3. Data

Our analysis draws on several administrative data sources. The main source is claims data from the Upper Austrian Health Insurance Fund (UAHIF), which contain comprehensive healthcare utilization and spending records for the universe of individuals insured through the private-sector social health insurance system in Upper Austria, including private-sector employees, unemployed

[1] In 2018, the last year of our data, job turnover was 9.6 percent for female workers and 9.3 percent for male workers, compared with European Union averages of 8.6 and 8.1 percent. The OECD employment protection legislation indicator for Austria is 1.7, the fifth-lowest among OECD countries; the United States ranks lowest at 1.3.

individuals, and retirees with private-sector employment histories, as well as their registered dependents. The dataset covers about 1.5 million individuals, corresponding to roughly 17 percent of the Austrian population, over the period 2006–2018. It contains detailed information on healthcare utilization, including physician visits, drug prescriptions, and hospital stays, together with the associated expenditures. Diagnoses are available for hospital stays and certified sick leaves and are coded according to the International Classification of Diseases (ICD-10), while drugs are classified using the Anatomical Therapeutic Chemical (ATC) system. Information on deaths is recorded directly in the insurance database, which allows us to identify the quarter of death for each decedent.

We use these data to construct a measure of end-of-life spending, defined as the total reimbursed inpatient, outpatient, and drug spending incurred during the four quarters preceding death. The measure captures all healthcare services covered by the insurance system but excludes in-home care that is not covered by health insurance. Because expenditures are recorded quarterly while deaths occur continuously, the quarter of death includes individuals who die early as well as those who die late, which leads to mechanically lower average spending for early deaths. To correct for this partial-exposure bias, we apply the adjustment proposed by Hoover et al. (2002), which rescales observed spending in the quarter of death to a full-quarter equivalent, ensuring comparability across decedents. Details on the estimation and implementation are provided in Appendix C.

We focus on the full population of decedents (N = 120,603) and, within this group, identify individuals with a terminal illness (N = 36,983). Following prior research (Lastrucci et al., 2018; Quinn et al., 2020, 2021), we define terminal illness as a progressive, incurable condition leading to irreversible health decline and death (Hui et al., 2014). Our analysis focuses on cancer and organ failure (i.e., somatic diseases), excluding cognitive or neurodegenerative conditions such as dementia.[2] For each terminal decedent, we define the diagnosis date as the first inpatient record of the condition in the hospital data, and for cancer cases, we also record the first observed cancer type. Because we do not observe the cause of death, we restrict the sample to individuals with repeated diagnoses of the same condition during the year preceding death, ensuring that death is attributable to the terminal illness rather than unrelated comorbidities.

Demographic characteristics and end-of-life spending across conditions are reported in Table B.1. The vast majority of deaths in our sample are attributable to cancer, accounting for around 62 percent of all terminal cases. Across most conditions, women represent a lower share of patients, with heart failure being the exception (55 percent). These patients are also the oldest at death, with an average age of around 75 years. At the opposite end of the spectrum, liver disease has the lowest share of women (29 percent) and the youngest average age at death, roughly 58 years. Survival after diagnosis ranges from 5.7 quarters for heart failure to 11.2 quarters for COPD.

[2] Terminal illnesses include cancer (C00–C97), heart failure (I50), chronic obstructive pulmonary disease (J40–J47), end-stage renal disease (N18–N19), and chronic liver disease or cirrhosis (K70–K77).

Second, we use individual-level social security records from the Austrian Social Security Database (ASSD) to construct family ties and measure spouses' labor market outcomes. The ASSD is a matched employer–employee dataset covering the universe of employment spells from 1972 to 2018. It provides daily information on labor market status, including employment, unemployment, retirement, sick leave, as well as annual wage data up to the social security contribution ceiling. The dataset also contains basic demographic characteristics such as age, gender and migrant status, and includes information on widow(er) pension receipt, although not on the benefit amount.

4. Trends and patterns in end-of-life spending

In this section, we examine key patterns in medical spending at the end of life. Using population-wide administrative data, we document how healthcare costs evolve near death and over time, and how these expenditures are distributed across individuals. Throughout, we analyze end-of-life spending for the full population of decedents and, separately, for the subset whose death is preceded by a terminal illness, to assess whether patterns and trends differ between terminal and non-terminal causes of death. We also distinguish between Hoover et al. (2002)-adjusted and unadjusted spending. These patterns position Austria within an international context, motivating our subsequent analysis of the mechanisms driving high end-of-life spending and its welfare implications.

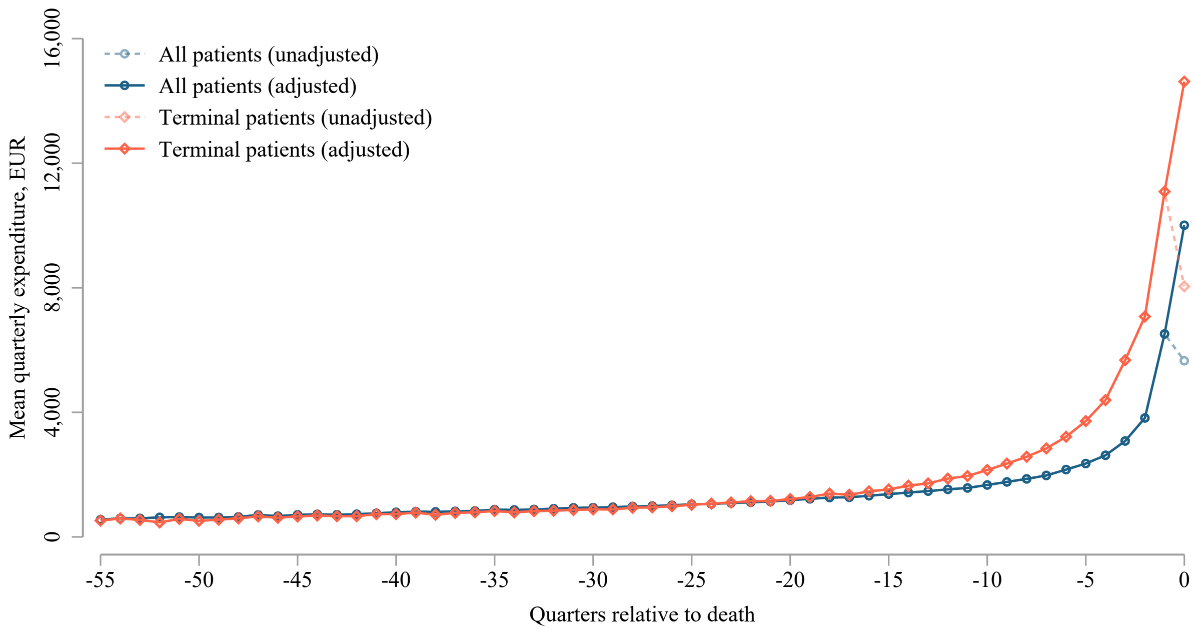
4.1. Medical spending is strongly concentrated at the end of life

Figure 1 traces quarterly medical spending in the periods leading up to death for all decedents and for individuals with a terminal diagnosis. Spending remains relatively modest over most of the life course but rises sharply as death approaches, making the final year a period of particularly intensive healthcare use. For the full sample of decedents, this increase in end-of-life spending is driven almost entirely by inpatient care, which accounts for approximately 80–90 percent of total expenditures in the final quarters, while outpatient services and prescription drugs contribute comparatively little (Figure A.1). Similar patterns have been documented across a range of health systems, where end-of-life expenditures are likewise concentrated in hospital-based care and are largely attributable to frequent, often low-intensity hospital admissions near death (French et al., 2017; Zeltzer et al., 2023).

Among patients with terminal diagnoses, spending levels exceed those of the overall decedent population several years prior to death, reflecting the progressive course of disease and the accumulation of symptoms over time. Even within the terminally ill population, spending trajectories are not uniform, with some diagnoses characterized by gradual increases and others by a more abrupt spending increase closer to death (Figure A.2).[3] Nevertheless, all diagnoses display

[3]This heterogeneity is consistent with established frameworks that distinguish end-of-life illness trajectories,

Figure 1 — Medical spending relative to death



Notes: The figure displays mean quarterly per-patient medical spending for all decedents and for individuals dying from a terminal illness, relative to the quarter of death. Spending is measured in euros and includes inpatient, outpatient, and prescription drug costs. Both unadjusted and Hoover-adjusted spending are reported; the latter imputes full-quarter expenditures for individuals who die partway through a quarter, ensuring comparability across quarters with different death timings (see Appendix Section C). Individual-level data are from the Upper Austrian Health Insurance Fund and cover the period 2006–2018.

a pronounced escalation in expenditures during the terminal phase, indicating substantially higher treatment intensity regardless of underlying condition.

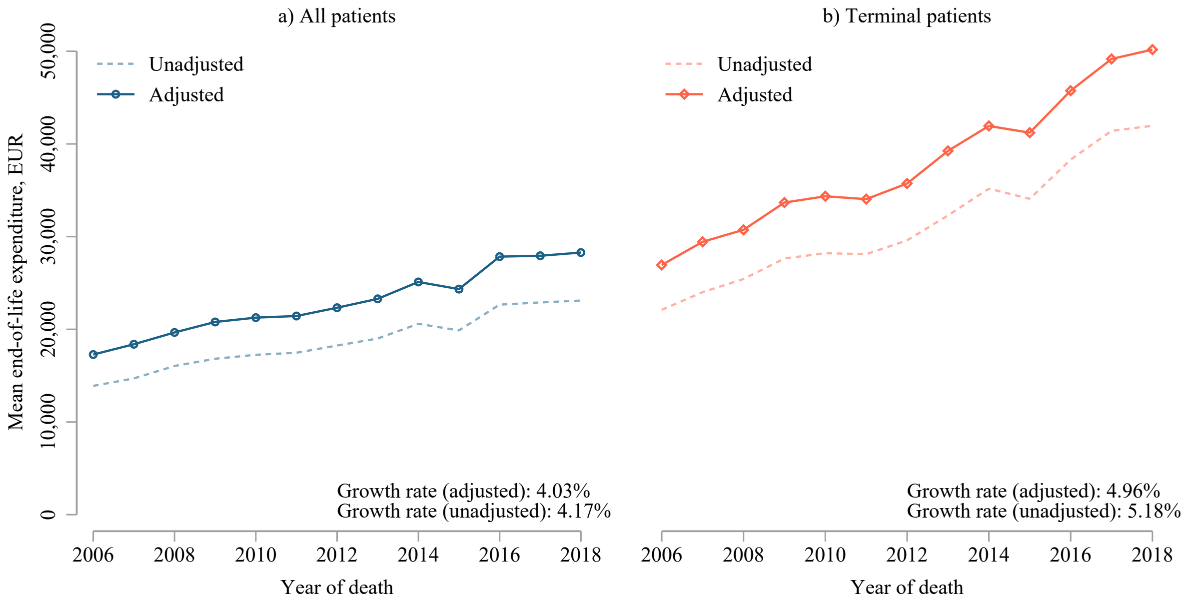
4.2. End-of-life spending has increased over time

In Figure 2, we aggregate medical spending per patient over the four quarters preceding death to illustrate how end-of-life medical expenditures have evolved over time.[4] Among all decedents, Hoover-adjusted end-of-life spending increased from 17,276 € in 2006 to 28,284 € in 2018, corresponding to an average annual growth rate of about four percent. Individuals with a terminal diagnosis exhibit substantially higher end-of-life costs, rising from 26,938 € in 2006 to 50,177 € in 2018, with a somewhat faster annual growth rate of roughly five percent. This pattern contrasts with evidence from U.S. Medicare showing little change over time in the spending share accounted for

including relatively abrupt terminal decline (e.g., cancer) and more prolonged, progressive or episodic courses (e.g., organ failure); see Lunney et al. (2003) and Murray et al. (2005).

[4]Disaggregated trends in end-of-life medical spending by inpatient, outpatient, and prescription drug expenditures are shown in Figure A.3.

Figure 2 — End-of-life medical spending between 2006–2018



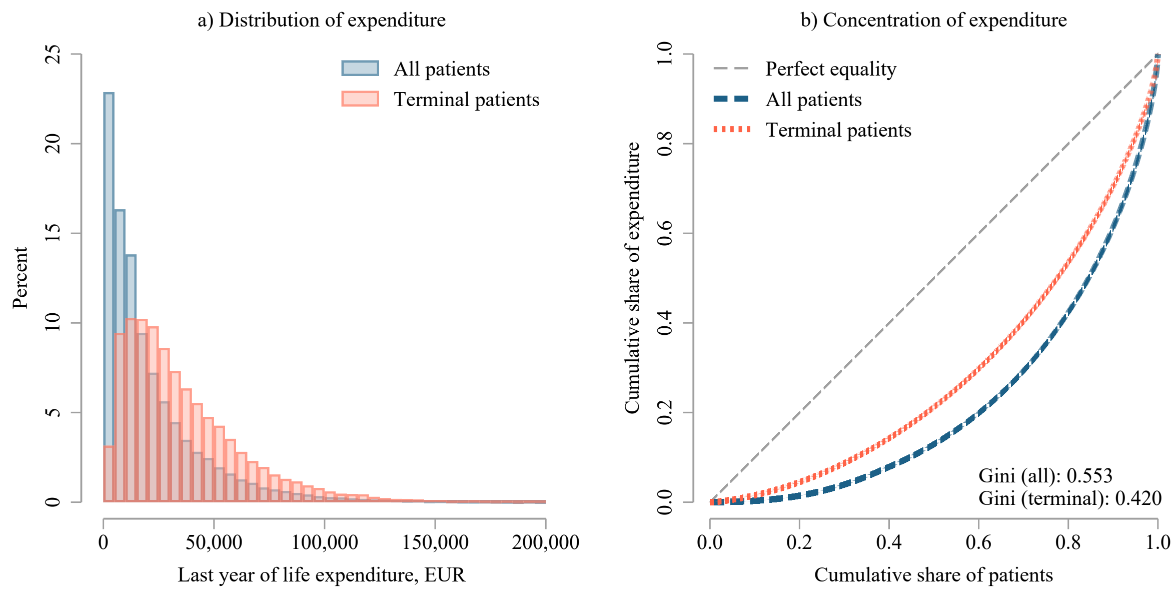
Notes: The figure displays the evolution of mean per-patient medical spending in the last year of life between 2006 and 2018 for all decedents (panel a) and for individuals dying from a terminal illness (panel b). The last year of life refers to the last four quarters before death. Spending is measured in euros and includes inpatient, outpatient, and prescription drug costs. Both unadjusted and Hoover-adjusted spending are reported; the latter imputes full-quarter expenditures for individuals who die partway through a quarter, ensuring comparability across quarters with different death timings (see Appendix Section C). Annual growth rates are calculated as the average annual percentage change in mean end-of-life spending, estimated using a log-linear regression of mean spending on a time trend. Individual-level data are from the Upper Austrian Health Insurance Fund and cover the period 2006–2018.

by beneficiaries in their last year of life (Riley and Lubitz, 2010). Despite the pronounced increase, Austria's end-of-life spending remains moderate by international standards, particularly relative to other high-income countries such as Germany or the United States (French et al., 2017).[5]

While average spending levels differ across diagnoses (Table B.1), the evolution of end-of-life spending over time is broadly similar across conditions. All major disease groups display a clear upward trend in end-of-life expenditures. Cancer patients have the highest average end-of-life spending (42,751 €), while heart failure patients have the lowest (26,582 €), with annual growth rates ranging from roughly 3 to 7 percent. Overall, these patterns are consistent with advances in medical technology, expanded access to high-cost treatments, and a general shift toward more intensive medical care at the end of life.

[5] In 2011, average per-capita end-of-life medical spending amounted to roughly 50,000 € in the United States and 45,000 € in Germany for inpatient, outpatient, and pharmaceutical services. Among European systems, Austria appears most similar to the Netherlands, where spending for these services was closer to 30,000 €.

FIGURE 3 — Distribution of end-of-life medical spending across patients



Notes: The figure displays the distribution (panel a) and concentration (panel b) of per-patient medical spending in the last year of life between 2006 and 2018 for all decedents and for individuals dying from a terminal illness. The last year of life refers to the last four quarters before death. Spending is measured in euros and includes inpatient, outpatient, and prescription drug costs. Hoover-adjusted spending is reported; the adjustment imputes full-quarter expenditures for individuals who die partway through a quarter, ensuring comparability across quarters with different death timings (see Appendix Section C). The distribution is shown for individuals with end-of-life spending below 200,000 €, using bins of width 5,000 €. Individual-level data are from the Upper Austrian Health Insurance Fund and cover the period 2006–2018.

4.3. End-of-life spending varies widely across patients

Figure 3 illustrates the substantial dispersion in medical spending during the last year of life. Panel a) shows that the distribution is strongly right-skewed: while most individuals incur moderate costs, a relatively small share accounts for very high expenditures. Average end-of-life spending amounts to 23,108 € for all decedents and 37,965 € for those with a terminal diagnosis, with corresponding standard deviations of 25,490 € and 28,819 €.

Panel b), which plots Lorenz curves of end-of-life spending, reveals an important nuance: while terminal patients exhibit higher absolute variation in spending levels, they display less relative inequality (Gini coefficient: 0.42 vs 0.55). Among all decedents, the top ten percent account for 38.6 percent of spending while the bottom 50 percent account for only 13.0 percent, reflecting the presence of many individuals who die with minimal healthcare utilization. In contrast, among terminal patients, the bottom 50 percent account for 21.2 percent and the top ten percent for 29.5 percent of spending. This more compressed distribution suggests that terminal illness creates a substantial "floor" of necessary medical care, though considerable variation persists above this baseline.

Part of this variation reflects differences across diagnostic groups. As shown in Table B.1, the degree of spending concentration varies across terminal conditions, with Gini coefficients ranging from 0.393 for cancer to 0.466 for liver disease. However, substantial within-diagnosis dispersion remains, indicating that end-of-life spending is shaped by factors beyond clinical severity alone. The next section examines these sources of variation in greater detail.

4.4. Why is end-of-life spending so high?

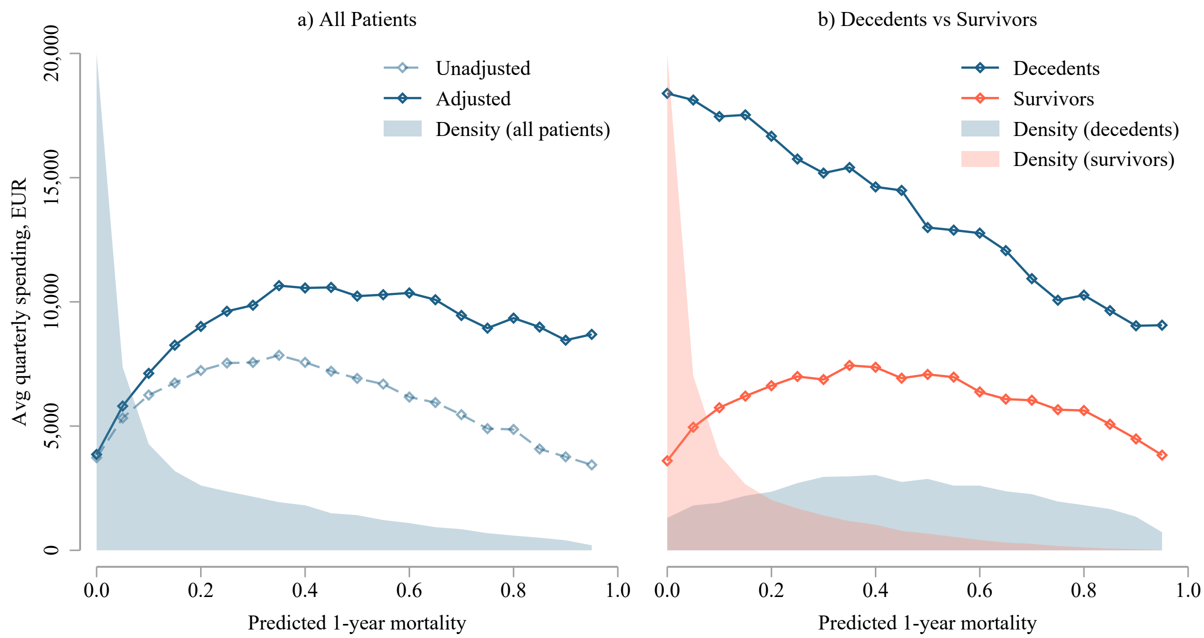
Having established the main descriptive patterns of end-of-life medical spending, we now examine the mechanisms behind these patterns. Our goal is to understand why so much is spent on individuals who die shortly thereafter and why spending varies so substantially across patients. Prior work by Zeltzer et al. (2023) shows that, even conditional on prognosis, patients who die within one year incur considerably higher medical costs than survivors, largely driven by recurrent, low-intensity hospitalizations. This raises questions about the efficiency of end-of-life care and the extent to which elevated spending reflects the severity of illness vs. treatment choices. We show that similar patterns hold for progressive terminal illness in our data and that differences in predicted mortality explain only a small fraction of socioeconomic variation in end-of-life spending.

Following Zeltzer et al. (2023), we begin by estimating a one-year mortality prediction at the time of diagnosis and examining how medical spending varies with predicted mortality risk, as shown in Figure 4. The prediction model incorporates demographic characteristics, baseline healthcare utilization, and clinical information observed at diagnosis, as described in Appendix Section D. Panel a) shows that the distribution of predicted mortality is highly right-skewed, with half of all patients having a predicted risk below ten percent. This suggests that most patients have relatively favorable baseline prognoses and that death is far from certain at that point. Average quarterly spending rises steadily with predicted mortality, increasing from around 4,000 € for low-risk patients to more than 10,000 € for those with higher predicted risk. After adjusting for the number of quarters alive, the difference between adjusted and unadjusted spending becomes more pronounced at higher mortality levels, reflecting that high-risk patients survive fewer quarters on average.[6]

In Panel b), we compare average quarterly spending between decedents and survivors across the predicted mortality distribution. Decedents have much higher predicted mortality risk than survivors (47 percent vs. 14 percent for survivors). Among survivors, spending follows an inverse-

[6]The adjusted measure applies the Hoover correction to rescale spending in the death quarter to a full-quarter equivalent (see Appendix C) and divides total first-year spending by quarters survived. The unadjusted measure divides total spending by four quarters.

FIGURE 4 — End-of-life medical spending by predicted mortality



Notes: The figure plots predicted one-year mortality against average quarterly medical spending in the year after diagnosis. Spending is measured in euros and includes inpatient, outpatient, and prescription drug costs. Panel a) compares adjusted and unadjusted spending for all patients. Adjusted spending is calculated using the Hoover adjustment, which imputes full-quarter expenditures for individuals who die partway through a quarter (see Appendix Section C), and is normalized by the number of quarters each patient was alive within the first year after diagnosis. Unadjusted spending is obtained by dividing total Hoover-adjusted annual spending by four. Panel b) compares adjusted spending between survivors and decedents. Individual-level data are from the Upper Austrian Health Insurance Fund and cover the period 2006–2018.

U shape, while for decedents, it is downward sloping, with substantial costs even when death is almost certain. As a result, the spending gap between the two groups is widest at the lower end of the predicted mortality distribution, where many deaths are unexpected and often trigger intensive, last-minute interventions.

Table 1 reports average spending and predicted mortality for decedents and survivors, and shows how the spending gap changes when survivor spending is reweighted to match the mortality-risk profile of decedents. On average, decedents spend 8,981 € more per quarter than survivors. The reweighting reduces the gap only slightly, to 8,556 €, implying that differences in baseline prognosis explain only around five percent of the spending differential. Of the remaining gap of 8,556 €, nearly all (97 percent) is accounted for by inpatient care, with outpatient physician services and pharmaceuticals contributing very little. Together, these patterns suggest that elevated end-of-life spending is driven less by underlying health differences than by the intensity of hospital-based care in the terminal phase, with unexpectedly high spending among lower-risk decedents and sustained

Table 1 — End-of-life medical spending and predicted mortality for decedents and survivors

Category	Average Quarterly Spending			Difference (Decedent - Survivor)			Mean
	Survivor Unweighted	Survivor Reweighted	Decedent	Raw Difference	Reweighted Difference	% of Total	Predicted Mortality
Total	4950	5376	13932	8981	8556	100.0	0.210
i. Inpatient	4357	4733	12993	8636	8260	96.5	0.210
ii. Doctor fees	167	173	303	136	130	1.5	0.210
iii. Drugs	426	471	636	210	166	1.9	0.210
a) Age group							
Q1 (15-52)	4423	4791	20748	16325	15957		0.054
Q2 (53-62)	5211	5767	16995	11783	11228		0.106
Q3 (63-70)	5389	5971	17877	12488	11906		0.148
Q4 (71-79)	5238	5656	15487	10249	9831		0.238
Q5 (80-100)	4257	4350	10555	6298	6205		0.535
Difference (Q5-Q1)	-166	-441	-10193	-10027	-9752		0.482
b) Gender							
Male	4738	5281	14835	10097	9554		0.213
Female	5168	5477	12967	7800	7491		0.207
Difference	430	196	-1867	-2297	-2064		-0.007
c) Education							
Non-university	4964	5386	13880	8916	8493		0.214
University	4636	5089	16540	11904	11451		0.114
Difference	-328	-298	2660	2988	2958		-0.100

Notes: The table reports average quarterly medical spending in the first year after diagnosis for decedents and survivors. "Raw Difference" denotes the unadjusted difference in spending between the two groups. "Reweighted Difference" adjusts survivor spending to match the mortality risk distribution of decedents, thereby controlling for differences in health status at diagnosis. "% of Total" shows each spending category's contribution to the overall reweighted difference, with components summing to 100 percent. "Mean Predicted Mortality" reports the average probability of death within one year, estimated from the probit model described in Appendix Section D. Adjusted spending is calculated using the Hoover adjustment, which imputes full-quarter expenditures for individuals who die partway through a quarter (see Appendix Section C), and is normalized by the number of quarters each patient was alive within the first year after diagnosis. All amounts are in euros.

intensive treatment for high-risk patients both contributing to the observed gap.

Finally, we extend the decomposition across demographic and socioeconomic groups to better understand why end-of-life spending varies so widely across patients. This exercise allows us to disentangle two potential sources of heterogeneity: (i) compositional differences, whereby certain groups may be systematically sicker or have worse prognoses at diagnosis, and (ii) differences in treatment intensity conditional on prognosis, whereby some groups may receive more aggressive care even when clinical risk is comparable.

Across age groups, predicted mortality increases steeply with age, while excess spending among decedents declines. The average spending difference for the oldest quintile (80–100 years of age) is 9,752 € lower than for the youngest quintile (15–52 years of age), suggesting that younger patients receive more intensive care conditional on prognosis. For gender, predicted mortality at diagnosis is nearly identical for men and women (21.3 vs. 20.7 percent), yet male decedents exhibit a 2,064 € higher spending gap, pointing to gender differences in treatment intensity. The pattern is even stronger across education groups. Highly educated patients have lower predicted mortality (11.4 percent vs. 21.4 percent) yet exhibit a 2,958 € higher spending gap, implying notably more intensive care despite a more favorable prognosis.

Taken together, these patterns show that clinical need explains only part of the variation in end-of-life spending. Instead, a substantial share reflects differences in treatment intensity, particularly hospital-based care, which also vary systematically with socioeconomic characteristics. This suggests that factors beyond the severity of illness, including patient preferences, family advocacy, health literacy, and provider behavior, likely play an important role in shaping end-of-life medical care.

5. Effects of spousal death on surviving spouses

Before turning to how differences in end-of-life spending shape survivor outcomes, we first establish the baseline effects of spousal death on surviving spouses' labor market and healthcare outcomes. We begin by describing our event study framework and the identifying assumptions underlying the comparison of spouses before and after death in section 5.1. We then present the main estimates of the dynamic response in employment and healthcare spending around spousal death in section 5.2. In Section 5.3 we provide robustness checks on these baseline estimates.

5.1. Event study specification

To estimate the causal effect of a spouse's death on the labor market and health outcomes of surviving spouses, we employ an event study design. We construct a sample of individuals whose spouse was diagnosed with a chronic terminal illness between 2006 and 2018 and follow them in a fully balanced panel for 16 quarters before and after the spouse's death.[7] Specifically, we estimate:

$$y_{it} = \sum_{k \neq -4} \tau_k \, \mathbb{I}\big(t - \bar{q}_{j(i)} = k\big) + \alpha_{\text{age}(i,t)} + \alpha_{\text{age}(j(i),t)} + \delta_t + \theta_{d(j(i))} + \varepsilon_{it}. \tag{1}$$

[7]For labor market outcomes, the sample consists of $N = 5{,}888$ couples with a terminal illness diagnosis. For health outcomes, we additionally require continuous insurance coverage of the surviving spouse in the UAHIF, yielding a sample of $N = 2{,}033$ individuals. We restrict the sample to surviving spouses who are observed continuously throughout the event window, ensuring that all estimated effects are not mechanically driven by the survivor's own mortality.

where y_{it} denotes the outcome of interest for surviving spouse i in calendar quarter t. The indicator function $\mathbb{I}(t - \bar{q}_{j(i)} = k)$ equals one if quarter t is k quarters relative to the death of spouse $j(i)$, where $\bar{q}_{j(i)}$ denotes the calendar quarter of death. The event time coefficients are estimated for $k = -16, -15, \ldots, 16$, omitting $k = -4$ (the fourth quarter before death) as the reference period. The coefficients of interest, $\hat{\tau}_k$, therefore capture estimated changes in outcomes at each relative time k compared to one year prior to the spouse's death.

To isolate these changes from confounding age-related and aggregate time trends, we include a rich set of fixed effects. Age fixed effects for the surviving spouse, $\alpha_{\text{age}(i,t)}$, control for systematic life-cycle patterns in outcomes, while age fixed effects for the deceased spouse, $\alpha_{\text{age}(j(i),t)}$, account for age-related differences in mortality risk and disease progression. Calendar-quarter fixed effects, δ_t, absorb common macroeconomic shocks and seasonality, and diagnosis-type fixed effects, $\theta_{d(j(i))}$, control for heterogeneity in treatment patterns and disease trajectories across terminal illnesses.[8]

The identifying assumption underlying this design is that, conditional on couples' age, calendar quarter, and diagnosis type, there would be no disruption in the outcome trends for the surviving spouse in the absence of the partner's death. Under this assumption, pre-death outcomes provide a plausible counterfactual for post-death outcomes at each quarter relative to the event. Deviations from this path can therefore be interpreted as causal effects of the spouse's death.

We acknowledge that end-of-life outcomes are part of a continuous disease process and that both diagnosis and disease progression may influence labor market and health behavior over an extended period (e.g. Böckerman et al. 2025; Fadlon and Nielsen 2019; Hodor 2021; Wang et al. 2023). In that sense, the end of life is not a separate medical event but reflects a worsening of the underlying illness. Our empirical approach does not aim to disentangle the effects of diagnosis from disease progression. Instead, it examines whether outcomes for surviving spouses change sharply around the time of death, beyond what would be expected from a gradual continuation of earlier trends. The absence of systematic pre-trends before the final year of life suggests that the observed changes are unlikely to be driven solely by gradual disease progression, and instead coincide with the terminal phase of illness.

As a robustness check for our baseline estimates, we follow Fadlon and Nielsen (2019, 2021) and exploit variation in the timing of spousal death to construct an explicit control group. In this design, individuals whose spouse has not yet died serve as controls for those whose spouse died earlier, so that treated and control individuals differ only in the timing of exposure to spousal death. This strategy provides a counterfactual that does not rely solely on pre-event trends within the treated

[8] A natural alternative would be to include individual fixed effects and rely solely on within-person variation over time. However, spousal death typically occurs at ages when labor market attachment is already declining sharply due to retirement. In this setting, a specification with individual fixed effects would mechanically conflate age-related life-cycle declines with the effects of spousal bereavement. Our preferred specification instead exploits comparisons across individuals observed at the same distance to spousal death, conditional on age and calendar time.

group, further reinforcing the credibility of our estimates. The empirical strategy and results are discussed in Section 5.3.

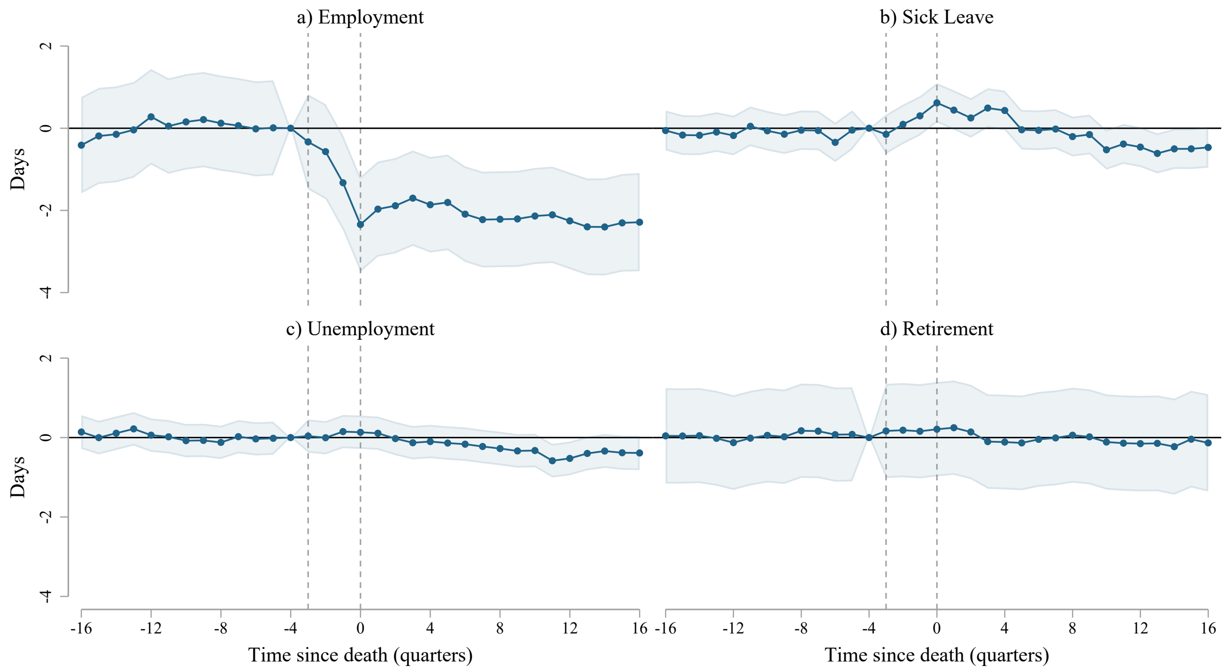
5.2. Results

We now estimate Equation (1) to trace the dynamic effects of spousal death on a range of labor market and healthcare utilization outcomes for surviving spouses. Before turning to the event study estimates, we summarize baseline characteristics to provide context for the magnitudes and interpretation of the dynamics that follow. Table B.2 reports outcomes measured prior to the last year of life: surviving spouses are on average around age 61 at the time of loss and many are already retired. Among those still active in the labor market, only 29 percent are in dual-earner households, and in more than half of these cases the surviving spouse earns the majority of household income. Baseline healthcare utilization is moderate, with 46 percent recording at least one outpatient visit. Finally, the illnesses preceding death are severe and protracted, lasting roughly two years on average, and predicted one-year mortality risk at diagnosis is about 51 percent. Together, these patterns indicate limited baseline labor market attachment and substantial healthcare needs entering the terminal phase, which we keep in mind when interpreting the event study profiles below.

Labor market attachment. We start by analyzing how spousal death affects surviving spouses' labor market outcomes. Theoretically, a spouse's health shock can lead to opposing adjustments in labor market behavior. Consistent with evidence on non-fatal health shocks, severe illness may reduce employment due to caregiving demands or shifts in how couples allocate time and resources when facing declining health and shortened life expectancy. At the same time, illness may increase labor supply incentives, either in an added-worker sense to compensate for lost household income or to cover rising medical expenses (Böckerman et al., 2025; Charles, 1999; Coile, 2004; García-Gómez et al., 2013; Hollenbeak et al., 2011; Jeon and Pohl, 2017; Shen et al., 2019). When illness ultimately leads to death, additional mechanisms come into play. Financial pressure to increase labor supply may be mitigated by strong social insurance (Böheim and Topf, 2020; Fadlon et al., 2019), while bereavement itself may induce temporary withdrawal from the labor market. Spousal death may also affect labor supply through preferences: salient mortality risk can raise the subjective time discount rate, shifting the labor-leisure tradeoff toward present utility and potentially reducing attachment to work (Ahammer et al., 2024). In what follows, we examine how these forces together unfold during the final phase of a progressive terminal illness in a setting characterized by generous social protection around death and bereavement.

Figure 5 traces changes in four labor market outcomes: employment, sick leave, unemployment,

Figure 5 — Event study estimates on labor market outcomes



Notes: Each figure displays the estimated effects of spousal death on surviving spouses' labor market outcomes from Equation (1). All labor market outcomes are measured in days, with zero assigned when an individual is not in the respective labor market state. Estimates are measured relative to the baseline of four quarters before death ($k = -4$). Shaded areas indicate 95 percent confidence intervals. Data on labor market outcomes are from the Austrian Social Security Database and cover the period 2006–2018.

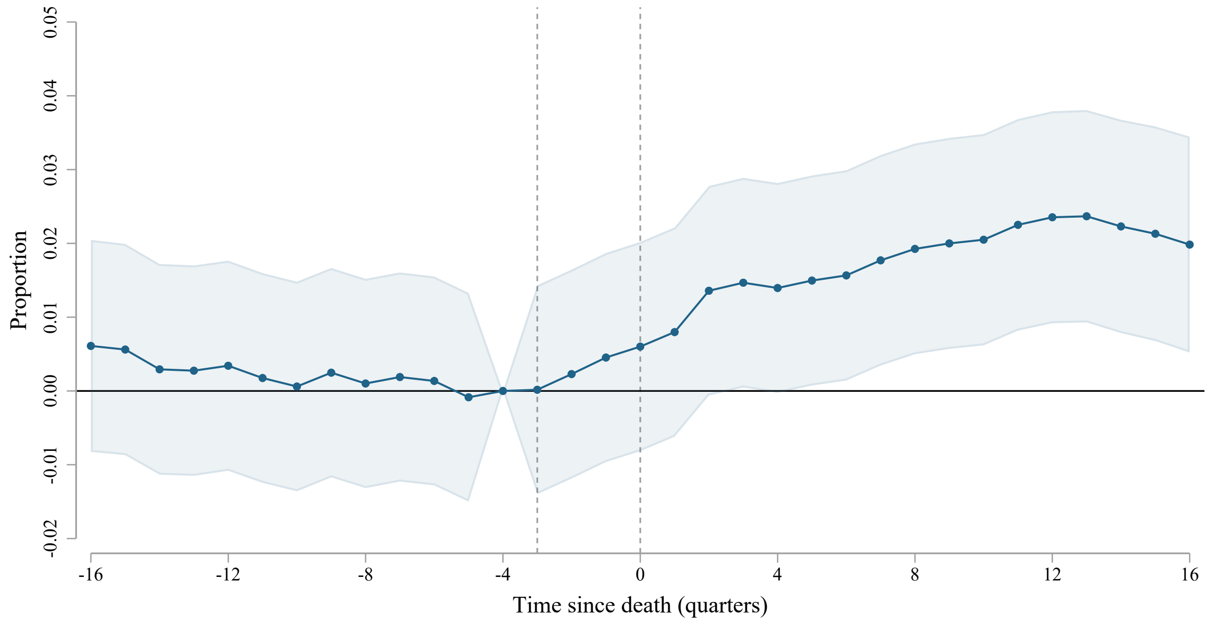
and retirement.[9] For each outcome, we report coefficient estimates $\hat{\tau}_k$ from Equation (1) together with 95 percent confidence bands. Vertical reference lines mark the last year of life and the quarter of death ($k = 0$). To capture both intensive and extensive margin adjustments, all outcomes are measured in days per quarter, with a value of zero when the individual is not in the respective labor market state.

Conditional labor market outcomes remain broadly stable until approximately one year prior to death. Beginning in the third quarter preceding the loss, employment starts to decline, with a pronounced drop in the quarter of death (panel a). At that point, surviving spouses work on average 2.3 fewer days per quarter, corresponding to a 7.3 percent decline relative to the baseline ($k = -4$). Although employment partially recovers thereafter, the reduction persists throughout the observation window and remains evident up to four years after death. This persistence suggests that the observed adjustments are not purely transitory responses to bereavement, but instead reflect longer-lasting changes in labor market attachment.

On the other hand, sickness absence follows a somewhat different pattern (panel b). It remains

[9] Corresponding event study estimates are reported in Table B.3.

FIGURE 6 — Event study estimates on the probability of leaving the labor force



Notes: Each figure displays the estimated effects of spousal death on surviving spouses' probability of leaving the labor force from Equation (1). "Out of the labor force" refers to not being in employment, unemployment, or retirement. Estimates are measured relative to the baseline of four quarters before death ($k = -4$). Shaded areas indicate 95 percent confidence intervals. Data on labor market outcomes are from the Austrian Social Security Database and cover the period 2006–2018.

largely unchanged before the loss, but rises sharply in the immediate aftermath of bereavement. In the quarter of death, sickness days increase by about 0.62 days per quarter, or roughly 38 percent relative to baseline levels. This increase fully dissipates by the second quarter after death, suggesting that, among those who remain employed, short-run adjustments to bereavement operate partly through temporary health- or stress-related absences from work covered by the social insurance system.

In contrast, we find no significant changes in unemployment (panel c) or retirement (panel d) either before or after the loss. This absence of reallocation across labor market states indicates that the sustained decline in employment days is unlikely to reflect transitions into unemployment or retirement. Instead, it points to a combination of short-term work interruptions and a more persistent exit from the labor force.

Figure 6 provides complementary evidence by examining the probability of being out of the labor force, defined as not being employed, unemployed, or retired in a given quarter. This probability begins to rise during the last year of life and becomes marginally significant starting in the second quarter after death. Four years later, it remains approximately 2 percentage points (pp) above baseline, corresponding to an increase of about 9 percent. To summarize, spousal death has a persistent negative effect on surviving spouses' employment that is largely driven by exits from the labor force, with no discernible medium-run changes in unemployment, retirement, or sick leave.

Physical and mental healthcare utilization. We next examine effects on survivors' healthcare utilization. These outcomes can be understood both as consequences of the loss in their own right and as potential mechanisms underlying the observed adjustments in labor market behavior. Previous research shows that health effects often arise both during the illness and after the loss. In the period leading up to death, caregiving demands and emotional strain can take a considerable toll on the spouse's physical and mental health (Arteaga et al., 2025; Bom et al., 2019; Böckerman et al., 2025; De Zwart et al., 2017), while newfound awareness of personal health risks has been shown to increase healthcare use and preventive behavior among close family members (Fadlon and Nielsen, 2019; Hodor, 2021; Wang et al., 2023). As the illness gives way to loss, several studies document marked physical and psychological consequences, though the magnitude and persistence of these effects vary across individuals and contexts. Deaths following chronic or terminal illness are generally associated with less severe and shorter-lived declines in well-being, as anticipation may partly cushion the emotional shock of bereavement (Morin et al., 2020; Shah et al., 2013; Siflinger, 2017).

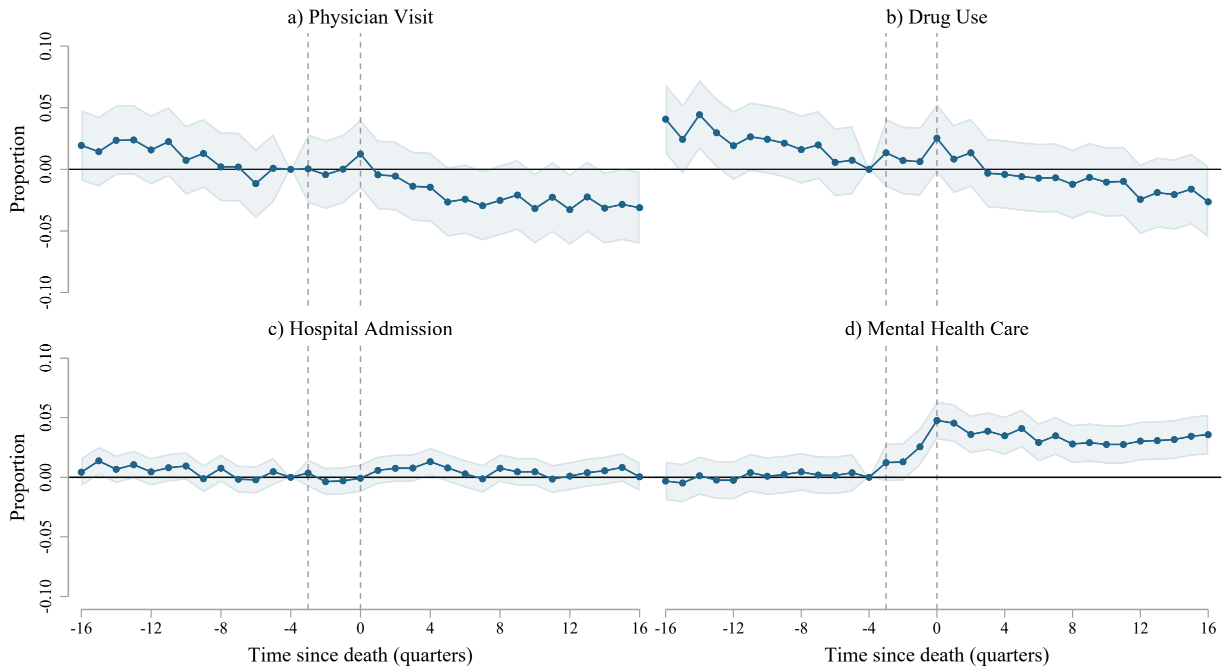
To better understand the health implications of spousal death, we examine how healthcare utilization among surviving spouses changes during the last year of life and in the period following the loss (Figure 7).[10] We examine four outcomes capturing distinct dimensions of healthcare demand: outpatient physician visits (panel a), prescription drug use (panel b), inpatient care (panel c), and mental healthcare utilization (panel d). As in the labor market analysis, estimates are reported relative to the fourth quarter before death, with vertical reference lines marking the last year of life and the quarter of death. All outcomes are measured as binary indicators, allowing us to focus on extensive-margin changes in healthcare utilization.

The results show no significant change around the time of death in the probability of outpatient visits, inpatient stays, or drug use. This absence of effects suggests that spousal death does not trigger major changes in surviving spouses' health that would translate into increased healthcare use at the extensive margin. It also rules out offsetting behavioral responses, such as increased contact with the healthcare system consistent with greater preventive behavior, or withdrawal from medical services due to distress or avoidance.

In contrast, we observe clear and pronounced responses in mental healthcare utilization. The probability of seeing a psychiatrist or psychologist or receiving antidepressant medication begins to rise already in the quarters leading up to death by 2.6 pp and peaks in the quarter of death at around 4.8 pp. This corresponds to an increase of approximately 80 percent relative to the mean one year before the loss. Although the effect gradually attenuates over time, it remains elevated even four

[10]Corresponding event study estimates are reported in Table B.4.

FIGURE 7 — Event study estimates on healthcare utilization



Notes: Each figure displays the estimated effects of spousal death on surviving spouses' healthcare utilization from Equation (1). Healthcare utilization is measured using indicator variables (0/1). Estimates are measured relative to the baseline of four quarters before death ($k = -4$). Shaded areas indicate 95 percent confidence intervals. Data on health outcomes are from the Upper Austrian Health Insurance Fund and cover the period 2006–2018.

years after bereavement, with an estimated increase of about 3.6 pp, or 60 percent.

Taken together, these patterns suggest that the health consequences of spousal death operate primarily through psychological distress, rather than through acute deterioration in physical health or broad changes in help-seeking behavior. Viewed alongside the labor market results, this distress likely contributes to both short-run reductions in labor market activity around bereavement and to more persistent declines in attachment thereafter.

5.3. Alternative identification strategy

As an alternative identification strategy, we provide Fadlon and Nielsen (2019, 2021) event study estimates. Specifically, for each individual who experiences a spouse's death in quarter t (the treated group), we identify individuals who will experience the same event 16 quarters later, in quarter $t + 16$. We classify these yet-to-be-treated individuals as controls by assigning them a placebo death in quarter t, when their spouse is still alive. This procedure is implemented for every quarter in the sample, allowing the same individuals to appear in both the treatment and control groups across different quarters, but never as their own control.

After constructing the treatment and control group, we estimate the following difference-in-differences event study model:

$$y_{it} = \sum_{k \neq -4} \tau_k^{FN} \, \mathbb{I}\big(t - \bar{q}_{j(i)} = k\big) \times T_i + \sum_k \iota_k \, \mathbb{I}\big(t - \bar{q}_{j(i)} = k\big) + \tilde{\alpha}_{\text{age}(i)} + \tilde{\alpha}_{\text{age}(j(i))} + \delta_t + \theta_{d(j(i))} + \xi_{it}, \quad (2)$$

where y_{it} denotes the outcome of individual i in quarter t, T_i indicates treatment status, and $\mathbb{I}\big(t - \bar{q}_{j(i)} = k\big)$ is a set of quarterly indicators relative to the spouse's actual or placebo death quarter $\bar{q}_{j(i)}$. The coefficients $\hat{\tau}_k^{FN}$ measure differences in outcomes at event time k between treated individuals and the control group, relative to the reference period $k = -4$ (one year before spousal death).

The model includes fixed effects for the surviving spouse's age evaluated at the actual or placebo death quarter ($\tilde{\alpha}_{\text{age}(i)}$) and for the deceased spouse's age evaluated at the same event quarter ($\tilde{\alpha}_{\text{age}(j(i))}$). These age controls address the fact that the placebo assignment shifts the timing of spousal death backward in calendar time, such that treated and control individuals differ mechanically in age at the event. We additionally include calendar-quarter fixed effects (δ_t), capturing shocks common to all individuals, and diagnosis-type fixed effects ($\theta_{d(j(i))}$) to control for differences in disease severity and progression across terminal illnesses. As an additional robustness check, we also estimate specifications that include individual fixed effects, which absorb time-invariant characteristics of the surviving spouse.

The key identifying assumption underlying this strategy is that, conditional on observables, the exact timing of a spouse's death within the four-year window is quasi-random. Under this assumption, treated and control individuals are comparable in characteristics and expectations prior to the shock, differing only in the timing of exposure.

We present the estimated effects in Figure A.4 and Figure A.5. For labor market outcomes, the baseline estimates closely align with those obtained under the alternative identification strategy, both with and without individual fixed effects. For healthcare outcomes, the main difference concerns the persistence of mental healthcare utilization effects. In the baseline specification, the increase in mental healthcare use remains statistically significant throughout the entire observation window, whereas under the alternative identification strategy the effect is statistically significant only during the first one to two years following spousal death. This difference may reflect a combination of declining utilization among treated individuals in later periods and a gradual increase in mental healthcare use among control individuals as they approach their own spouse's death.

6. How end-of-life medical spending shapes survivor outcome trajectories

Having estimated the average effects of spousal death on labor market and health outcomes, we now examine whether these effects vary with the intensity of end-of-life medical spending. Section 6.1 describes how we construct our measure of excess end-of-life spending. Section 6.2 lays out our main dose response event study specification and the identifying assumptions underlying the approach. Section 6.3 presents the main results. Section 6.4 examines heterogeneity by age, gender, and education. Section 6.5 reports robustness checks, including alternative measures of treatment intensity, Fadlon and Nielsen (2019, 2021) estimates, and instrumental variables estimates that exploit provider-level variation in excess medical spending to address potential endogeneity in end-of-life spending.

6.1. Calculating treatment intensity

Having estimated the average effects of spousal death on labor market and health outcomes, we next examine whether these effects vary with the intensity of end-of-life medical spending. As documented in Section 4.4, medical spending in the last year of life exhibits substantial heterogeneity even among patients with similar predicted mortality at diagnosis, suggesting that part of this variation reflects treatment choices rather than clinical need alone. To capture this discretionary component, we construct an individual-level measure of excess end-of-life spending by comparing each decedent's total expenditure in the last year of life with a counterfactual level representing the expected spending had the patient continued to receive non-terminal care.

For each decedent j, observed spending is defined as total expenditure in the final four quarters before death, denoted S_j. The counterfactual is constructed using survivors who (i) lived at least as long as the decedent, (ii) had the same ICD-10 diagnosis, and (iii) had a similar predicted mortality risk at the time of diagnosis.[11] Survivors are evaluated at the same number of quarters since diagnosis as the decedent's reference point, ensuring that spending is compared at equivalent points along the disease trajectory. To avoid comparing decedents' terminal care to survivors' own terminal care, a survivor is eligible as a control only if at least four additional quarters of observed survival remain at the matched comparison point. A graphical example of the matching timeline is provided in Figure A.6.[12]

[11] Predicted mortality risk is estimated at diagnosis using a probit model described in Appendix Section D. Patients are grouped into 50 mortality-risk bins to facilitate comparisons among individuals with similar ex-ante prognoses.

[12] We restrict the analysis to decedents who survive at least three quarters after diagnosis when constructing end-of-life measures, ensuring that observed spending reflects a complete four-quarter terminal window. Because the longest observed survival among eligible control individuals is 51 quarters, valid counterfactuals can be constructed only for decedents who survive up to 47 quarters after diagnosis. Individuals with longer survival durations are excluded from

Under these criteria, the counterfactual for decedent j is defined as the mean spending of all eligible survivors in the matched set $\mathcal{M}(j)$:

$$\widehat{S}_j = \frac{1}{|\mathcal{M}(j)|} \sum_{s \in \mathcal{M}(j)} S_s. \tag{3}$$

Excess end-of-life spending is then calculated as:

$$\Delta_j = S_j - \widehat{S}_j. \tag{4}$$

The resulting measure captures variation in end-of-life spending beyond what would be expected given diagnosis, prognosis, and disease duration, and is interpreted as reflecting discretionary or aggressive treatment intensity. Note that, if there was no idiosyncratic component to spending, so that spending is fully determined by the matching criteria, we would have $S_j = \widehat{S}_j$ for all j and therefore $\Delta_j = 0$. Importantly, this measure is not intended to distinguish between the underlying sources of excess spending, but rather to summarize the overall intensity of medical care received during the terminal phase. In Section 6.5, we assess the robustness of our findings by considering alternative scalings of end-of-life spending and alternative definitions of the counterfactual.

In Table B.5 we report covariate balance between decedents and matched survivors. The matching procedure performs well along the key matching dimensions: predicted mortality risk and time from diagnosis are virtually identical between the two groups, indicating close alignment in ex-ante prognoses and disease trajectories. Demographic characteristics not used in the matching procedure are also generally well balanced. Small differences remain in age at diagnosis and nationality, but these imbalances are modest in magnitude and unlikely to materially affect our estimates.[13] Average excess end-of-life spending among decedents amounts to 35,963 €.

6.2. Main event study specification

To assess whether spillover effects of spousal death depend on treatment intensity, we extend Equation (1) by interacting the event time indicators with excess spending:

$$\begin{aligned} y_{it} = &\sum_{k \neq -4} \beta_k \, \mathbb{I}\big(t - \bar{q}_{j(i)} = k\big) \cdot \Delta_{j(i)} + \sum_{k \neq -4} \eta_k \, \mathbb{I}\big(t - \bar{q}_{j(i)} = k\big) \\ &+ \alpha_{\text{age}(i,t)} + \alpha_{\text{age}(j(i),t)} + \delta_t + \theta_{d(j(i))} + \zeta_{it}. \end{aligned} \tag{5}$$

Here, $\Delta_{j(i)}$ denotes excess end-of-life spending of individual i's deceased spouse j, measured

the analysis. To ensure stable estimates, we require at least five matched survivors per decedent-time cell.

[13] If anything, the fact that decedents are slightly older than matched survivors would bias estimates of excess end-of-life spending downward, since younger individuals tend to receive more intensive care conditional on predicted mortality (see Section 4.4).

in units of 1,000 €, and all remaining terms are the same as in Equation (1). Excess spending is defined at the individual level and is time-invariant across the event window. The coefficients of interest, $\hat{\beta}_k$, capture how outcomes around spousal death differ across surviving spouses whose partners experienced more versus less intensive end-of-life care. This specification allows us to assess whether spillover effects vary systematically with excess end-of-life spending.

Identification of the $\hat{\beta}_k$s in Equation (5) relies on excess spending being as-good-as-randomly assigned across surviving spouses after conditioning on our rich set of covariates. Put differently, we assume that $\Delta_{j(i)}$ primarily captures idiosyncratic variation in end-of-life spending rather than systematic differences in underlying disease severity that also predict spouses' trajectories around death. Two features of our design help support this assumption. First, our specification absorbs very flexible age effects for both spouses and diagnosis fixed effects for the decedent, so identification comes from comparisons among couples in which the deceased partners are of similar age and die from the same cause. Second, $\Delta_{j(i)}$ is constructed as "excess" spending relative to a counterfactual benchmark that conditions on diagnosis, predicted mortality risk at diagnosis, and disease duration, so it captures spending above what would be expected given observables at the onset and evolution of the terminal illness. In Section 6.5 we further assess robustness to alternative constructions of excess spending and, most importantly, present instrumental variables estimates that use provider-level variation in treatment intensity to address remaining concerns about endogeneity in $\Delta_{j(i)}$.

6.3. Results

We now test whether the changes in spouses' labor market and health trajectories documented in Section 5 vary with the decedent's excess end-of-life spending. The expected direction of these spillovers is theoretically ambiguous. More spending could reflect care that shifts responsibilities away from family members, reducing informal caregiving demands and easing short-run time constraints. At the same time, higher-intensity care may increase coordination costs by generating more frequent admissions and short-notice medical events, along with repeated trips to and from the hospital. Any time effects on work can be compounded by financial pressure if end-of-life care tightens household liquidity through out-of-pocket costs and contemporaneous earnings or wealth losses around the time of death. Treatment intensity may also affect spouses' health via stress, uncertainty, and the burden of end-of-life decision-making, with knock-on effects on healthcare use and labor supply. Finally, greater contact with the healthcare system during the terminal phase may mechanically shift survivors' own utilization by lowering the fixed costs of accessing care and increasing diagnosis and treatment of previously unmet needs.

Against this backdrop, we estimate Equation (5) and report dose response event study estimates $\hat{\beta}_k$ for labor market outcomes (employment, sick leave, unemployment, and retirement) and healthcare utilization (outpatient visits, prescription drugs, inpatient admissions, and mental healthcare)

Figure 8 — Event study estimates on labor market outcomes by end-of-life medical spending

Notes: Each figure displays the estimated effects of end-of-life medical spending on surviving spouses' labor market outcomes from Equation (5). All labor market outcomes are measured in days, with zero assigned when an individual is not in the respective labor market state. Coefficients can be interpreted as changes in outcome trajectories per additional 1,000 € of excess end-of-life spending. Estimates are measured relative to the baseline of four quarters before death ($k = -4$). Shaded areas indicate 95 percent confidence intervals. Data on labor market outcomes are from the Austrian Social Security Database and cover the period 2006–2018.

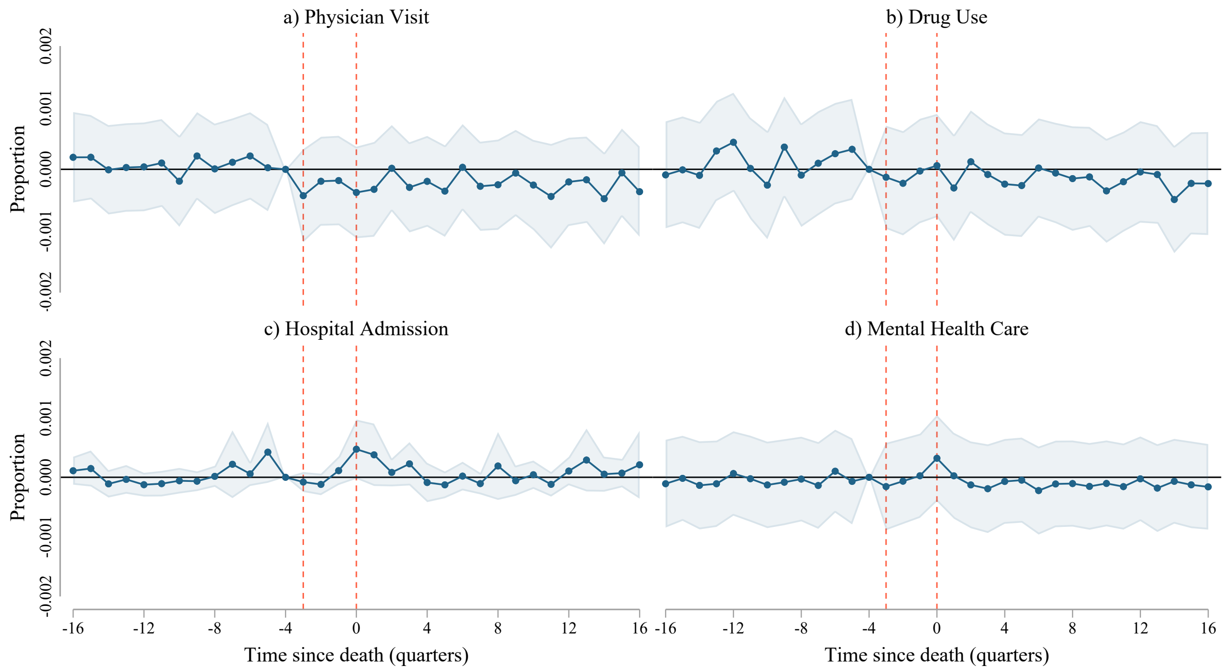
in Figures 8 and 9.[14] The figures plot the interaction coefficients, $\hat{\beta}_k$, which measure how the change in each outcome at event time k varies with the decedent's excess spending. Quantitatively, $\hat{\beta}_k$ can be interpreted as the effect of an additional 1,000 € of excess end-of-life spending on the survivor's outcome trajectory, relative to the reference quarter $k = -4$.

Across all outcomes, we find no evidence that spouses' responses vary with the level of excess end-of-life spending. The estimated interaction effects are small and statistically indistinguishable from zero throughout the event window. Conditional on prognosis, survival duration, and diagnosis, higher treatment intensity does not translate into detectable differences in survivors' labor market behavior, healthcare utilization, or mental health.

To assess whether specific types of medical care matter, we estimate separate interaction models for inpatient, outpatient, and prescription drug spending. Across all components, the interaction effects remain small and statistically insignificant, indicating that variation in treatment intensity within any single spending category does not lead to differential labor market or health responses

[14]Corresponding event study estimates are reported in Table B.6 and Table B.7.

Figure 9 — Event study estimates on healthcare utilization by end-of-life medical spending



Note: Each figure displays the estimated effects of end-of-life medical spending on surviving spouses' healthcare utilization from Equation (5). Healthcare utilization is measured using indicator variables (0/1). Coefficients can be interpreted as changes in outcome trajectories per additional 1,000 € of excess end-of-life spending. Estimates are measured relative to the baseline of four quarters before death ($k = -4$). Shaded areas indicate 95 percent confidence intervals. Data on health outcomes are from the Upper Austrian Health Insurance Fund and cover the period 2006–2018.

among surviving spouses (Tables B.8 and B.9). We further allow the effects to vary across the excess-spending distribution by estimating models separately by spending quintile, but again find no systematic differences across low- and high-spending groups (Tables B.10 and B.11).

Taken together, these results suggest that the large and persistent changes we document around spousal death are driven by the shock of illness and loss itself rather than by marginal differences in the intensity of medical spending during the terminal phase. One interpretation is that the channels through which end-of-life care could affect survivors—caregiving time, stress and uncertainty, and financial pressure—are either weak in this institutional setting, offsetting across mechanisms, or too small relative to the dominant effects of the impending and realized death to generate detectable differences in spouses' trajectories. From a welfare perspective, the absence of measurable survivor spillovers implies that variation in end-of-life spending is unlikely to be justified by improvements in dependents' economic or health outcomes, strengthening the case that at least some of the observed spending dispersion reflects low-value or wasteful care rather than benefits that extend to the household.

6.4. Heterogeneity

The results so far show that a spouse's end-of-life period has sizeable and lasting consequences for surviving partners, yet these consequences do not vary systematically with the level of medical spending in the final year of life. However, the end-of-life experience is unlikely to be homogeneous across households. Demographic and socioeconomic characteristics may shape caregiving demands, exposure to income loss, and the resources available to buffer financial and psychological stress. As a result, even if treatment intensity does not matter on average, it could still differentially affect adjustment for particular groups.

To better understand this pattern, we examine heterogeneity across observable spousal characteristics. Specifically, we divide the sample at the median age at death (61 years), distinguishing between younger and older surviving spouses. This cutoff roughly corresponds to the boundary between the working-age population and individuals near or past retirement in the Austrian context. We also compare responses by gender and by educational attainment, distinguishing between individuals with and without a college degree. For each subgroup, we estimate a baseline event study specification (Equation 1) alongside an event study specification that allows event time effects to vary with excess end-of-life medical spending (Equation 5). Results are presented in Tables B.12–B.14 for labor market outcomes and Tables B.15–B.17 for healthcare outcomes.

The heterogeneity analysis indicates some variation in how spouses respond to the illness progression and the subsequent loss. Labor market adjustments are more pronounced among women, who tend to carry a larger share of caregiving responsibilities, younger spouses with greater scope to adjust labor supply, and those with lower education. These groups experience larger reductions in employment and are more likely to exit the labor force altogether. Differences in healthcare utilization are comparatively modest, although mental health effects appear more concentrated among women, older spouses, and those with no university degree. Finally, although end-of-life medical spending varies substantially across patients, this variation does not meaningfully alter the estimated effects. Consistent with the average results, higher treatment intensity does not appear to affect labor market or health responses for any of the subgroups we have examined.

6.5. Robustness

This section presents several robustness checks to assess the sensitivity of our findings. First, we assess the sensitivity of our results to alternative constructions of treatment intensity by using different measures of excess end-of-life medical spending. Second, we exploit differences in provider practice styles as a robustness check to account for potential endogeneity in end-of-life care intensity.

Alternative treatment intensity measures. We construct alternative measures of treatment intensity to assess whether our findings are sensitive to how end-of-life spending is scaled. While the baseline measure uses total spending in the last four quarters of life, we construct two additional versions. The first adjusts for incomplete observation by computing average quarterly spending in the last year of life, dividing total spending in the last year of life by the number of observed quarters. This accounts for the roughly 7 percent of patients who are not observed for all four quarters, either due to late entry (diagnosis occurring close to death) or because no claims are observed in some final quarters, for example due to home-based palliative care. Using average rather than the sum of spending avoids mechanically assigning lower treatment intensity to these individuals solely because we observe them for fewer quarters.

The second measure captures treatment intensity over the full disease trajectory by computing average quarterly spending from diagnosis to death. This allows us to assess whether treatment intensity accumulated over the full course of illness, rather than only in the final year of life, is associated with differential spillover effects.

Next, we assess the robustness of our baseline measure of excess spending by varying the definition of the counterfactual. While the baseline estimates rely on the time-aligned matching approach described above (i.e., conditioning on diagnosis, predicted mortality at diagnosis, and time since diagnosis) we also construct two simpler alternative counterfactuals.

The first alternative compares observed last-year-of-life spending with average non-terminal spending among survivors with the same diagnosis, pooling all post-diagnosis observations. Excess spending is then defined as:

$$\Delta_j^{\text{simple}} = S_j - 4 \cdot \bar{s}_{\text{survivor},\, d(j)}, \tag{6}$$

where S_j denotes total medical spending in the last year of life for decedent j, and $\bar{s}_{\text{survivor},\, d(j)}$ is the average per-quarter medical spending among survivors with the same diagnosis $d(j)$. This measure captures how much more is spent in the final year of life relative to typical post-diagnosis spending for that disease, abstracting from differences in prognosis and disease duration.

The second counterfactual uses a regression-based prediction of expected non-terminal spending. Specifically, we regress survivors' mean quarterly healthcare spending after diagnosis on demographics at diagnosis (age, sex, nationality, and education), baseline healthcare utilization prior to diagnosis, clinical characteristics (diagnosis and comorbidity burden), and predicted mortality risk at diagnosis. The regression is estimated using survivors only, so that predicted spending reflects healthcare utilization in the absence of end-of-life care.

Applying the vector of estimated coefficients $\hat{\Pi}$ to the corresponding characteristics X_j of decedent j yields a predicted level of non-terminal quarterly spending, $\hat{s}_j^{\text{reg}} = X_j'\hat{\Pi}$. To make this prediction comparable to observed last-year-of-life spending, we scale it to an annual amount by multiplying by four quarters, $\hat{S}_j^{\text{reg}} = 4 \cdot \hat{s}_j^{\text{reg}} = 4 \cdot X_j'\hat{\Pi}$. The corresponding excess spending measure is then defined as:

$$\Delta_j^{\text{reg}} = S_j - \hat{S}_j^{\text{reg}} = S_j - 4 \cdot X_j'\hat{\Pi}. \tag{7}$$

This approach allows expected spending to vary flexibly with observable characteristics and prognosis, while abstracting from the precise timing of disease progression within the year. It therefore provides an intermediate benchmark between the diagnosis-based comparison and the fully time-aligned matching approach used in the baseline analysis.

Tables B.18 and B.19 report estimates based on five alternative measures of end-of-life medical spending, combining three definitions of treatment intensity with two alternative constructions of the counterfactual. Across all specifications, dynamic effects from Equation (5) on surviving spouses' labor market outcomes and healthcare utilization are small and insignificant, and joint F-tests fail to reject the null that all post baseline event study coefficients are jointly equal to zero. Static specifications that collapse the post last-year-of-life period into a single indicator occasionally yield statistically significant estimates, but these effects are economically small, sensitive to specification choice, and not supported by the dynamic estimates. Overall, the results provide no consistent evidence that higher end-of-life medical spending has meaningful spillover effects on surviving spouses' labor supply or healthcare utilization, regardless of its definition.

Alternative identification strategy. As an additional robustness check, we re-estimate the treatment-intensity effects using the event study approach of Fadlon and Nielsen (2019, 2021), introduced in Section 5.3. Rather than relying on within-individual pre-event trends, this approach exploits quasi-random variation in the timing of spousal death across otherwise comparable individuals. We extend this framework by interacting event-time indicators with the excess end-of-life spending measure defined in Section 6.1, allowing us to examine whether the dynamic effects of spousal death vary with treatment intensity under this alternative source of identification.

Formally, we estimate the following fully-interacted difference-in-differences event study specification:

$$\begin{aligned} y_{it} = &\sum_{k \neq -4} \beta_k^{FN}\, \mathbb{I}\big(t - \bar{q}_{j(i)} = k\big) \times \Delta_{j(i)} \times T_i + \sum_{k \neq -4} \kappa_k\, \mathbb{I}\big(t - \bar{q}_{j(i)} = k\big) \times \Delta_{j(i)} \\ &+ \sum_{k \neq -4} \phi_k\, \mathbb{I}\big(t - \bar{q}_{j(i)} = k\big) \times T_i + \tilde{\alpha}_{\text{age}(i)} + \tilde{\alpha}_{\text{age}(j(i))} + \delta_t + \theta_{d(j(i))} + \zeta_{it}, \end{aligned} \tag{8}$$

where y_{it} denotes the outcome of individual i in quarter t, $\mathbb{I}\big(t - \bar{q}_{j(i)} = k\big)$ is an indicator for quarter k relative to the spouse's actual or placebo death, $\bar{q}_{j(i)}$, with $k = -4$ as the omitted reference period, $\Delta_{j(i)}$ denotes excess end-of-life spending of spouse $j(i)$, as defined in Section 6.1, and T_i is an indicator equal to one for treated individuals and zero for not-yet-treated controls.

The specification includes age fixed effects for the surviving spouse ($\tilde{\alpha}_{\text{age}(i)}$) and the deceased spouse ($\tilde{\alpha}_{\text{age}(j(i))}$) evaluated at the event quarter, calendar-quarter fixed effects (δ_t), and diagnosis fixed effects ($\theta_{d(j(i))}$). The coefficients $\hat{\beta}_k^{FN}$ capture how the effect of spousal death at event time k varies with excess end-of-life spending, measured in units of 1,000 €. As before, we also provide results with individual-level fixed effects, which absorb time-invariant heterogeneity across spouses. Standard errors are clustered at the individual level.

Table B.20 (labor market outcomes) and Table B.21 (healthcare outcomes) report the resulting estimates with and without individual fixed effects. Across specifications, the estimated interaction effects remain small and statistically insignificant, reinforcing the conclusion that variation in end-of-life treatment intensity does not generate meaningful spillover effects on surviving spouses' labor market or health outcomes.

Hospital treatment intensity as an instrument. Because nearly all excess end-of-life medical spending occurs in inpatient settings (97 percent), we exploit variation in hospitals' treatment intensity as a source of plausibly exogenous variation in end-of-life spending in an instrumental variables (IV) setting. A large literature documents substantial and persistent variation in end-of-life care intensity across hospitals and regions, even among patients with comparable ex-ante mortality risk. This variation is commonly interpreted as reflecting differences in provider practice styles rather than patient preferences or underlying health (Fisher et al., 2003*a*; Landrum et al., 2008; Teno et al., 2005; Zhang et al., 2023).

To isolate provider-driven variation in end-of-life spending, we assign each patient to the hospital where they received most end-of-life inpatient care and instrument end-of-life spending with a hospital-level measure of treatment intensity. Following Section 6.1, this measure constructs hospital-level excess spending within diagnosis-mortality-risk bins by comparing inpatient spending among decedents to spending among observationally similar survivors treated at the same hospital, omitting decedents in our sample in a leave-one-out style calculation.[15]

In this specification, we focus on the average effect of end-of-life spending on survivors' outcomes rather than on dynamic responses and, because identification no longer rests on pre-trends, we drop the pre-end-of-life period and aggregate outcomes over quarters $t \geq -4$. Let $\bar{y}_i$ denote the resulting aggregated outcome, and let $S_{j(i)}$ denote the deceased spouse's total inpatient medical

[15]For each hospital, observed spending is defined as average inpatient spending per quarter in the last year of life among decedents treated at that hospital. Counterfactual spending is constructed using survivors treated at the same hospital with the same disease diagnosis and predicted mortality-risk bin, evaluated at the same number of quarters since diagnosis. Survivors are required to have at least one inpatient admission at that hospital during the corresponding four-quarter comparison window. Excess spending is defined as the difference between observed decedent spending and this counterfactual mean.

spending in the last year of life. We estimate the following two-stage least squares specification:

$$\bar{y}_i = \rho\, S_{j(i)} + X_i'\Psi + \theta_{d(j(i))} + \lambda_{y(j(i))} + u_i, \tag{9}$$

$$S_{j(i)} = \omega\, Z_{j(i)} + X_i'\Gamma + \theta_{d(j(i))} + \lambda_{y(j(i))} + v_i, \tag{10}$$

where $Z_{j(i)}$ captures hospital treatment intensity as described above.[16] The vector X_i includes age-group fixed effects for both the surviving spouse and the deceased spouse. The specification further includes year-of-death fixed effects $\lambda_{y(j(i))}$ and disease-type fixed effects $\theta_{d(j(i))}$. Standard errors are clustered at the hospital level.

Interpreting $\hat{\rho}$ as the causal effect of end-of-life medical spending on surviving spouses' outcomes requires instrument relevance and a valid exclusion restriction, namely that hospital treatment intensity affects spouses only through the care received by the deceased partner. A primary concern is endogenous sorting of patients with worse unobserved health or stronger family advocacy into higher-intensity hospitals. We mitigate this concern by conditioning on detailed diagnosis fixed effects and predicted mortality risk at diagnosis, and by constructing the hospital-level instrument within narrowly defined patient groups. Consistent with prior evidence that risk-adjusted variation in end-of-life medical spending largely reflects provider practice styles rather than patient demand or care quality (Zhang et al., 2023), the IV estimates can be interpreted as local average treatment effects driven by hospital practice styles.[17]

Tables B.22 and B.23 report two-stage least squares estimates for labor market and healthcare outcomes, respectively. For labor market outcomes, the first-stage relationship between hospital treatment intensity and end-of-life medical spending is strong, yet the IV estimates show no statistically or economically meaningful effects. For healthcare outcomes, the first stage is weaker but still informative, and the corresponding IV estimates remain close to zero and statistically insignificant.

Overall, the IV results reinforce the conclusions from the event study analysis. Although end-of-life medical spending varies substantially across hospitals, our IV estimates show no evidence that such hospital-driven variation in spending affects surviving spouses' labor market or healthcare outcomes.

7. Conclusion

Medical spending is highly concentrated at the end of life and varies widely across patients, even conditional on diagnosis and predicted health status. This paper first documents the level,

[16] Both $S_{j(i)}$ and $Z_{j(i)}$ are measured in 1,000 €.

[17] Note that these IV estimates are not directly comparable to our baseline dose-response event-study estimates. They should instead be viewed as complementary evidence that variation in end-of-life spending does not materially affect survivor outcomes when identification comes from a different source.

composition, and growth of end-of-life spending in Austria and then asks whether treatment intensity in the terminal phase has spillover effects on surviving spouses. Using administrative healthcare claims linked to labor market records, we begin by estimating the dynamic effects of spousal death on spouses' employment and healthcare utilization and then test whether these trajectories vary with a decedent-specific measure of excess end-of-life spending, defined relative to a counterfactual benchmark of non-terminal care.

We find that end-of-life spending is quantitatively important and has risen sharply over time, with substantial dispersion across patients that is only weakly explained by prognosis. We also document sizeable and persistent responses to spousal death, including a sustained decline in employment and a pronounced increase in mental healthcare use. However, these labor market and health trajectories are essentially unchanged across the distribution of excess end-of-life spending. The same null pattern holds when we isolate inpatient, outpatient, and drug spending and when we allow for non-linear effects by estimating separately across spending quintiles.

These findings are informative for the broader debate on the value of intensive end-of-life care. While additional treatment may be warranted if it improves patient survival or quality of life, existing evidence has raised concerns that aggressive end-of-life interventions often deliver limited clinical benefit and may worsen patient and caregiver well-being, whereas less intensive and palliative approaches can improve comfort and psychosocial outcomes and may sometimes modestly prolong survival (Fisher et al., 2003*a*,*b*; Landrum et al., 2008; Temel et al., 2010; Wright et al., 2008; Zhang et al., 2023). Our analysis cannot speak to survival effects because it conditions on death, but it speaks directly to a distinct welfare-relevant margin: benefits that operate through household spillovers. The absence of measurable spillovers onto spouses' labor market and health outcomes implies that variation in end-of-life spending is unlikely to be justified by improvements in dependents' economic or health trajectories.

Taken together, the results suggest that the large and persistent changes around spousal death are driven by the shock of illness and loss itself rather than by marginal differences in treatment intensity during the terminal phase. One interpretation is that the channels through which end-of-life care could affect survivors, including caregiving time, stress and uncertainty, and financial pressure, are either weak in this institutional setting, offsetting across mechanisms, or small relative to the dominant effects of impending and realized death. From a welfare perspective, the lack of detectable survivor benefits strengthens the case that at least some of the observed dispersion in end-of-life spending reflects low-value or wasteful care rather than meaningful gains that extend to the household.

These conclusions have two policy implications. First, efforts to improve value in end-of-life care should not be evaluated solely on spending reductions, but on whether they maintain or improve patient-centered outcomes while avoiding costly care that does not deliver commensurate benefits.

Second, policies that shift care away from default hospital-based pathways toward earlier palliative integration, better care coordination, and clearer decision support may improve allocative efficiency even if they do not materially change spouses' subsequent labor market and health trajectories. In that sense, the case for reform can rest on improving patient experience and reducing low-value utilization, without relying on additional benefits through surviving family members.

A caveat is that our administrative data do not allow us to directly unpack the mechanisms behind our findings. Distinguishing whether treatment intensity matters through caregiving time and coordination burdens, household financial exposure, or changes in stress, uncertainty, and end-of-life decision-making would require information we do not observe, such as direct measures of caregiving inputs and travel time, household balance sheets, or expectations and well-being. Understanding these channels is important for designing interventions that improve end-of-life care while supporting families, and we view this as a natural direction for future research.

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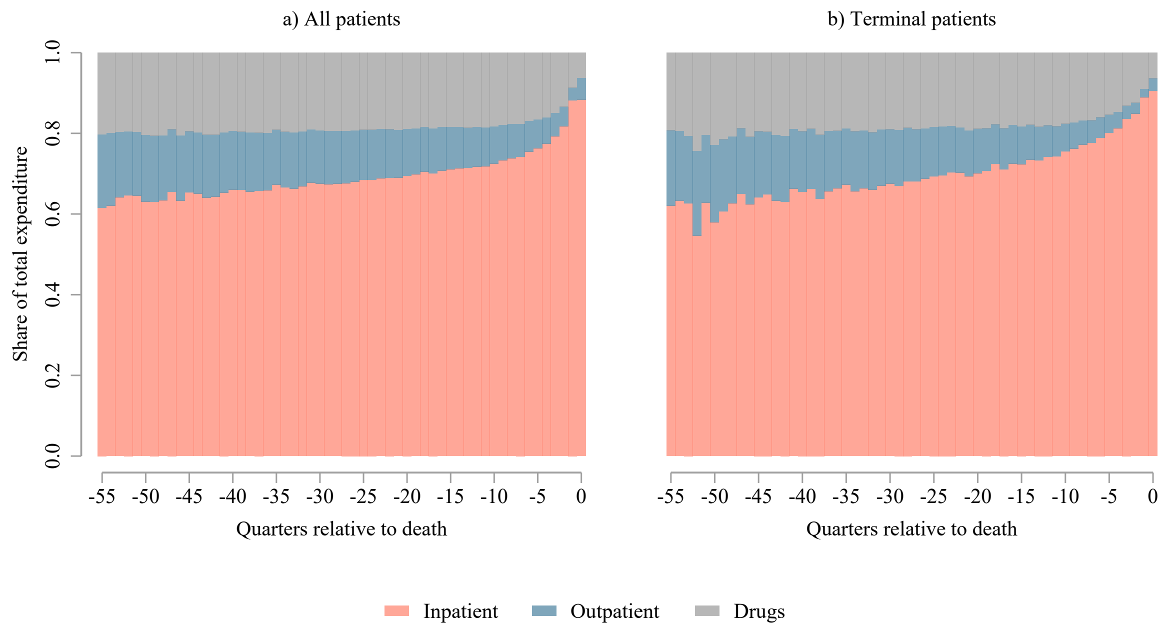
Web appendix

This web appendix contains additional material for the paper *"End-of-life medical spending: Patterns and household spillovers"* by Alexander Ahammer and Lea-Karla Matic.

Contents

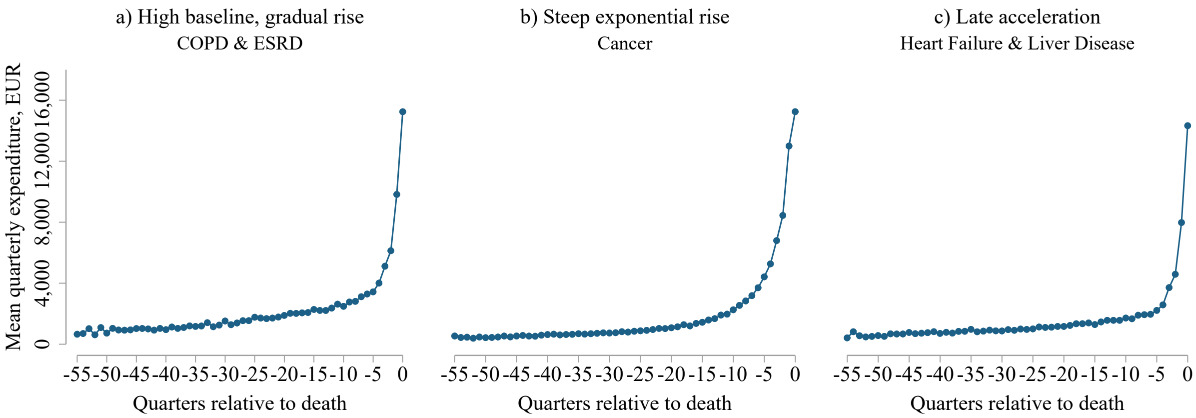
A. Additional figures

Figure A.1 — Medical spending relative to death, by type of service



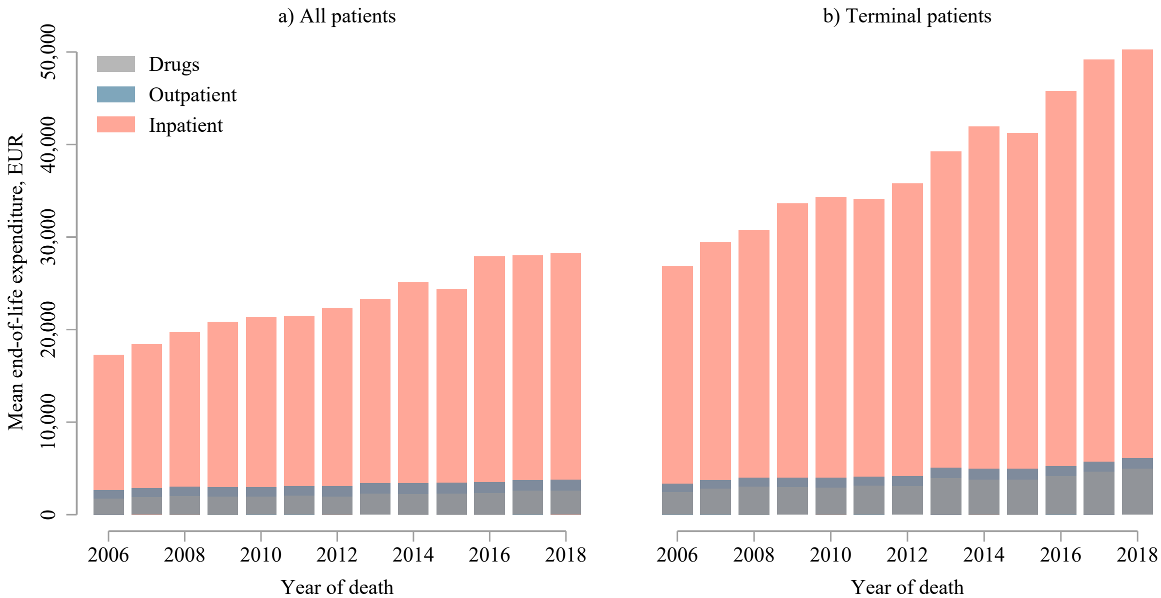
Notes: The figure displays the share of quarterly medical spending allocated to inpatient, outpatient, and prescription drug costs for all decedents (panel a) and for individuals dying from a terminal illness (panel b), relative to the quarter of death. Spending is Hoover-adjusted; the adjustment imputes full-quarter expenditures for individuals who die partway through a quarter, ensuring comparability across quarters with different death timings. Individual-level data are from the Upper Austrian Health Insurance Fund and cover the period 2006–2018.

Figure A.2 — Medical spending relative to death, by disease trajectory



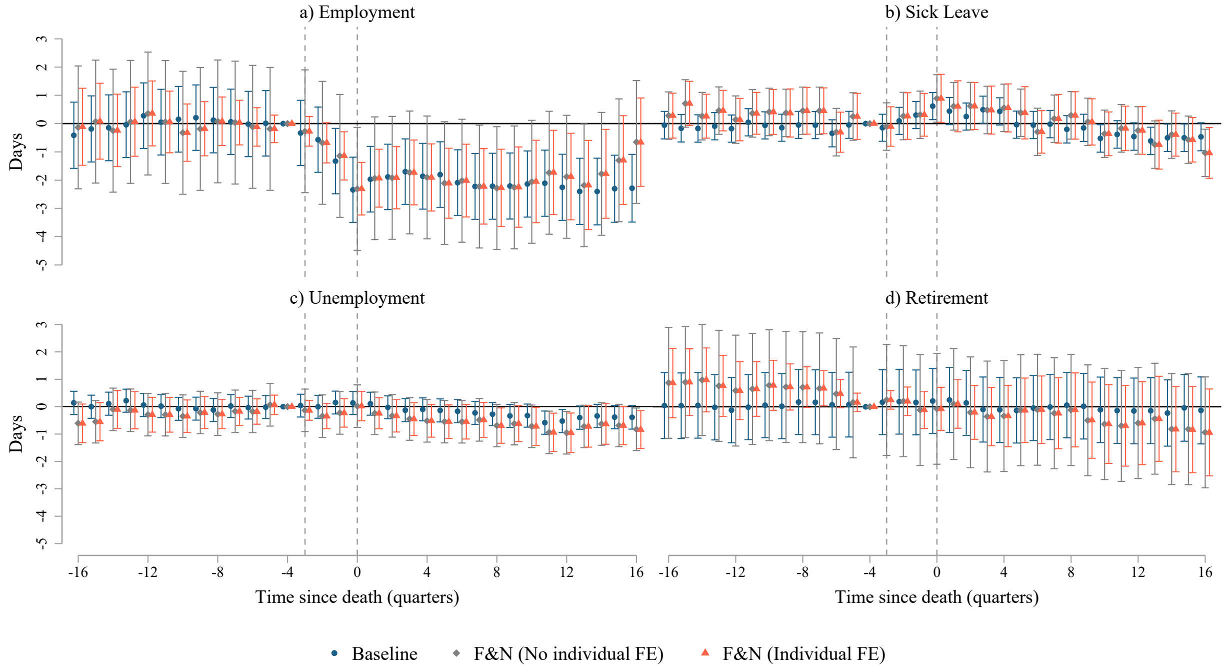
Notes: The figure displays mean quarterly per-patient medical spending for individuals dying from a terminal illness, relative to the quarter of death, by disease. Diseases are grouped by spending patterns across panels a)–c). Spending is measured in euros and includes inpatient, outpatient, and prescription drug costs. Individual-level data are from the Upper Austrian Health Insurance Fund and cover the period 2006–2018. COPD = Chronic Obstructive Pulmonary Disease, ESRD = End-Stage Renal Disease.

Figure A.3 — Trend in end-of-life medical spending 2006–2018, by type of service



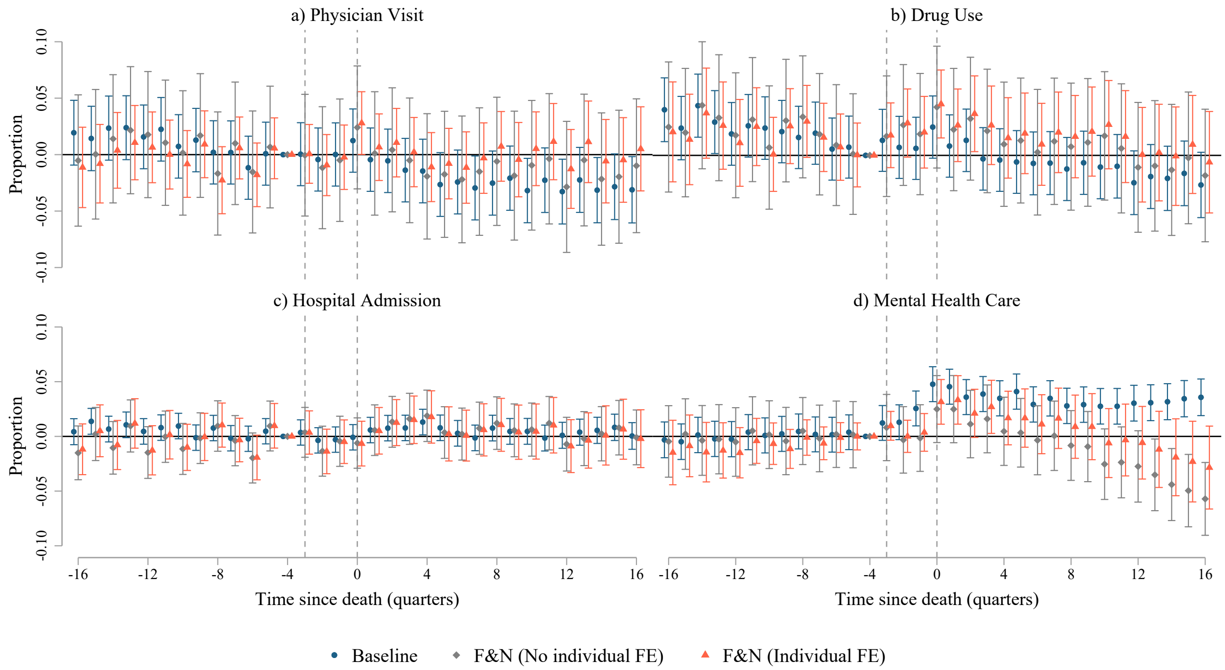
Notes: The figure displays the evolution of mean per-patient medical spending in the last year of life between 2006 and 2018 for all decedents (panel a) and for individuals dying from a terminal illness (panel b), by type of service (inpatient, outpatient, and prescription drug costs). Spending is Hoover-adjusted; the adjustment imputes full-quarter expenditures for individuals who die partway through a quarter, ensuring comparability across quarters with different death timings. Individual-level data are from the Upper Austrian Health Insurance Fund and cover the period 2006–2018.

FIGURE A.4 — Event study estimates on labor market outcomes, alternative identification strategy



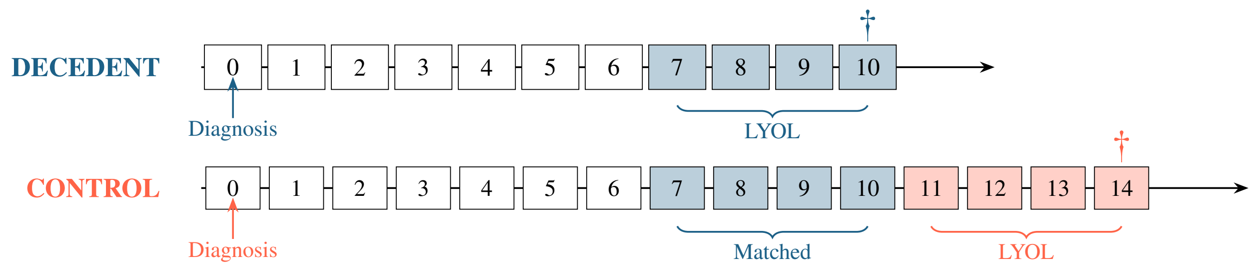
Notes: Each figure displays the estimated effects of end-of-life medical spending on surviving spouses' labor market outcomes from Equation 1 (baseline) and Equation 2 (Fadlon and Nielsen), estimated with and without individual fixed effects. All labor market outcomes are measured in days, with zero assigned when an individual is not in the respective labor market state. Estimates are measured relative to the baseline of four quarters before death ($k = -4$). Shaded areas indicate 95 percent confidence intervals. Data on labor market outcomes are from the Austrian Social Security Database and cover the period 2006–2018.

FIGURE A.5 — Event study estimates on healthcare utilization, alternative identification strategy



Notes: Each figure displays the estimated effects of end-of-life medical spending on surviving spouses' healthcare utilization from Equation 1 (baseline) and Equation 2 (Fadlon and Nielsen), estimated with and without individual fixed effects. Healthcare utilization is measured using indicator variables (0/1). Estimates are measured relative to the baseline of four quarters before death ($k = -4$). Shaded areas indicate 95 percent confidence intervals. Data on health outcomes are from the Upper Austrian Health Insurance Fund and cover the period 2006–2018.

Figure A.6 — Excess end-of-life medical spending construction



Notes: The figure illustrates the time-aligned matching procedure. For each decedent, spending is measured in the last year of life. A matched control group is then selected from survivors who (i) share the same diagnosis, (ii) belong to the same predicted mortality risk bin at diagnosis, and (iii) are observed at the same number of quarters since diagnosis but have not yet entered their own last year of life (i.e., they have at least four additional quarters of observed survival). This procedure is repeated for each decedent, and counterfactual spending is defined as the average spending among all eligible matched survivors.

B. Additional tables

Table B.1 — Descriptive statistics by disease

	Disease Category					
	Cancer	COPD	Heart Failure	ESRD	Liver Disease	All
Panel A: Demographics						
N	23,022	2,958	7,790	1,453	1,760	36,983
Share of terminal deaths (%)	62.3	8.0	21.1	3.9	4.8	100.0
Female (%)	44.7	41.4	54.9	48.8	28.8	46.0
University education (%)	2.8	1.1	1.6	1.0	1.7	2.3
Age at death	63.8	69.7	75.4	70.3	57.9	66.7
Mean survival (quarters)	7.8	11.2	5.7	6.9	7.8	7.6
Panel B: Last Year of Life Expenditure						
Mean expenditure (EUR)	42,751	32,123	26,582	40,320	33,779	37,965
Share of inpatient care (%)	84.9	84.1	85.2	85.6	88.3	85.1
Share of outpatient care (%)	4.2	5.7	6.6	5.1	4.7	4.9
Share of drugs (%)	10.9	10.2	8.2	9.3	7.0	10.0
Standard deviation	35,012	30,534	26,589	36,926	41,604	34,168
Bottom 50% share (%)	22.9	21.4	21.4	20.7	19.2	21.2
Top 10% share (%)	27.6	31.1	31.7	31.0	34.7	29.5
Gini coefficient	0.393	0.425	0.428	0.434	0.466	0.420
Annual growth rate (%)	5.19	4.11	3.52	3.43	6.77	4.96

Notes: The table presents descriptive statistics for terminal patients in the last year of life, stratified by disease category. The last year of life is defined as the last four quarters before death. All expenditures are Hoover-adjusted; the adjustment imputes full-quarter expenditures for individuals who die partway through a quarter, ensuring comparability across quarters with different death timings, and are reported in euros. Mean expenditure and standard deviation are calculated for patients with last year of life expenditure below 200,000 €. The annual growth rate is calculated as the average annual percentage change in mean last year of life expenditure over the sample period, estimated using a log-linear regression of mean expenditure on a time trend. Data on terminal diagnoses and expenditures are from the Upper Austrian Health Insurance Fund and cover the period 2006–2018. COPD = Chronic Obstructive Pulmonary Disease, ESRD = End-Stage Renal Disease.

Table B.2 — Descriptive statistics: spousal panel

Variables	Mean	Std. dev.
a) Demographic characteristics		
Female	0.65	0.48
Austrian	0.98	0.14
University degree	0.04	0.20
Own age at death	61.08	10.76
b) Household characteristics		
Children	0.606	0.489
Dual earning household	0.287	0.452
Own income share	0.562	0.400
Primary earner	0.552	0.497
c) Labor market outcomes		
Employment days	34.82	43.90
Unemployment days	2.31	13.16
Retirement days	31.93	43.41
Sickness absence days	1.67	13.81
Out of labor force	0.21	0.41
d) Health outcomes		
Physitian visit	0.458	0.498
Drug use	0.354	0.478
Hospital admission	0.036	0.187
Mental health care	0.059	0.235
e) Spouse illness characteristics		
Spouse age at death	63.28	10.57
Quarters since spouse diagnosis	8.70	9.88
Predicted mortality	0.51	0.27
Excess LYOL spending (EUR 1000)	47.72	47.08
Individuals		5,888 (2,033)
Person-quarter observations		76,544 (26,429)

Notes: The table reports descriptive statistics for individuals whose spouse was diagnosed with a chronic terminal illness between 2006 and 2018. Means and standard deviations are calculated using observations prior to the reference quarter ($k = -4$). Labor market and demographic characteristics are based on the full sample of $N = 5{,}888$ individuals. Health outcomes are reported for the subsample of continuously insured individuals in the Upper Austrian Health Insurance Fund (UAHIF; $N = 2{,}033$). Labor market data are from the Austrian Social Security Database, and health data are from the UAHIF; both sources cover the period 2006–2018.

Table B.3 — Event study estimates on labor market outcomes

	Employment (1)	Sick Leave (2)	Unemployment (3)	Retirement (4)	Out of LF (5)
t=-16	-0.4122	-0.0550	0.1398	0.0426	0.0061
t=-15	-0.1876	-0.1658	-0.0017	0.0395	0.0056
t=-14	-0.1482	-0.1721	0.1094	0.0490	0.0029
t=-13	-0.0397	-0.0927	0.2186	-0.0198	0.0028
t=-12	0.2773	-0.1762	0.0609	-0.1273	0.0034
t=-11	0.0515	0.0465	0.0192	-0.0150	0.0018
t=-10	0.1542	-0.0624	-0.0779	0.0569	0.0006
t=-9	0.2095	-0.1463	-0.0717	0.0196	0.0025
t=-8	0.1226	-0.0479	-0.1222	0.1717	0.0010
t=-7	0.0627	-0.0557	0.0225	0.1624	0.0019
t=-6	-0.0152	-0.3436	-0.0344	0.0737	0.0014
t=-5	0.0100	-0.0457	-0.0175	0.0800	-0.0009
t=-4	0.0000	0.0000	0.0000	0.0000	0.0000
t=-3	-0.3320	-0.1478	0.0377	0.1661	0.0002
t=-2	-0.5690	0.0947	-0.0040	0.1856	0.0023
t=-1	-1.3268**	0.3014	0.1501	0.1584	0.0045
t=0	-2.3426***	0.6179**	0.1338	0.2098	0.0060
t=1	-1.9677***	0.4411*	0.1087	0.2478	0.0080
t=2	-1.8855***	0.2506	-0.0255	0.1403	0.0136*
t=3	-1.7013***	0.4913	-0.1298	-0.1011	0.0147**
t=4	-1.8622***	0.4319	-0.1004	-0.1135	0.0140*
t=5	-1.8057***	-0.0369	-0.1379	-0.1348	0.0150**
t=6	-2.0903***	-0.0510	-0.1661	-0.0447	0.0157**
t=7	-2.2238***	-0.0190	-0.2253	-0.0090	0.0177**
t=8	-2.2147***	-0.2029	-0.2764	0.0591	0.0193***
t=9	-2.2067***	-0.1534	-0.3366	0.0182	0.0200***
t=10	-2.1358***	-0.5242***	-0.3267	-0.1124	0.0205***
t=11	-2.1075***	-0.3837*	-0.5829***	-0.1407	0.0225***
t=12	-2.2543***	-0.4579**	-0.5255**	-0.1531	0.0235***
t=13	-2.3989***	-0.6122***	-0.4000*	-0.1463	0.0237***
t=14	-2.4018***	-0.5016**	-0.3395	-0.2284	0.0223***
t=15	-2.3024***	-0.5011**	-0.3819*	-0.0410	0.0213***
t=16	-2.2863***	-0.4664**	-0.3880*	-0.1338	0.0198***
Observations	207,624	207,624	207,624	207,624	207,624
Mean outcome (t=-4)	32.1019	1.6382	2.2037	34.7000	0.2183
Effect t=-2 (%)	-1.77	5.78	-0.18	0.53	1.05
Effect t=0 (%)	-7.30	37.72	6.07	0.60	2.75
Effect t=8 (%)	-6.90	-12.38	-12.54	0.17	8.82
Effect t=16 (%)	-7.12	-28.47	-17.61	-0.39	9.09
Disease FE	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes
Spouse age FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes

Notes: The table displays the estimated effects of end-of-life medical spending on surviving spouses' labor market outcomes from Equation (1). All labor market outcomes are measured in days, with zero assigned when an individual is not in the respective labor market state. Estimates are measured relative to the baseline of four quarters before death ($k = -4$). Data on labor market outcomes are from the Austrian Social Security Database and cover the period 2006–2018. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE B.4 — Event study estimates on healthcare utilization

	Physician Visit (1)	Drug Use (2)	Hospital Admission (3)	Mental Health Care (4)
t=-16	0.0194	0.0407***	0.0043	-0.0032
t=-15	0.0143	0.0243*	0.0138**	-0.0048
t=-14	0.0235	0.0443***	0.0067	0.0013
t=-13	0.0239*	0.0297**	0.0106*	-0.0023
t=-12	0.0157	0.0192	0.0046	-0.0025
t=-11	0.0224	0.0264*	0.0080	0.0039
t=-10	0.0073	0.0244*	0.0095	0.0009
t=-9	0.0129	0.0212	-0.0012	0.0023
t=-8	0.0020	0.0160	0.0076	0.0045
t=-7	0.0019	0.0198	-0.0017	0.0018
t=-6	-0.0116	0.0056	-0.0022	0.0015
t=-5	0.0008	0.0073	0.0047	0.0038
t=-4	0.0000	0.0000	0.0000	0.0000
t=-3	0.0004	0.0134	0.0036	0.0123
t=-2	-0.0043	0.0071	-0.0036	0.0129*
t=-1	0.0001	0.0063	-0.0029	0.0255***
t=0	0.0124	0.0252*	-0.0008	0.0477***
t=1	-0.0044	0.0083	0.0058	0.0454***
t=2	-0.0055	0.0134	0.0076	0.0359***
t=3	-0.0137	-0.0031	0.0077	0.0387***
t=4	-0.0145	-0.0041	0.0131**	0.0348***
t=5	-0.0265*	-0.0059	0.0078	0.0410***
t=6	-0.0242*	-0.0072	0.0028	0.0292***
t=7	-0.0295**	-0.0069	-0.0014	0.0348***
t=8	-0.0252*	-0.0121	0.0076	0.0279***
t=9	-0.0208	-0.0066	0.0046	0.0290***
t=10	-0.0318**	-0.0104	0.0046	0.0275***
t=11	-0.0226	-0.0097	-0.0015	0.0275***
t=12	-0.0327**	-0.0244*	0.0010	0.0304***
t=13	-0.0224	-0.0189	0.0039	0.0308***
t=14	-0.0314**	-0.0205	0.0055	0.0317***
t=15	-0.0284*	-0.0160	0.0083	0.0345***
t=16	-0.0311**	-0.0264*	0.0004	0.0357***
Observations	69,498	69,498	69,498	69,498
Mean outcome (t=-4)	0.4658	0.3523	0.0328	0.0598
Effect t=-2 (%)	-0.93	2.02	-11.11	21.61
Effect t=0 (%)	2.67	7.16	-2.54	79.72
Effect t=8 (%)	-5.41	-3.44	23.23	46.63
Effect t=16 (%)	-6.68	-7.48	1.13	59.74
Disease FE	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes
Spouse age FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes

Notes: The table displays the estimated effects of end-of-life medical spending on surviving spouses' healthcare utilization from Equation (1). Healthcare utilization is measured using indicator variables (0/1). Estimates are measured relative to the baseline of four quarters before death ($k = -4$). Data on health outcomes are from the Upper Austrian Health Insurance Fund and cover the period 2006–2018. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE B.5 — Matching balance and excess end-of-life spending

Variable	Decedents	Survivors	Difference	SMD
Panel A: Covariate Balance				
Mortality risk	0.5190	0.5188	0.0002	0.001
Time from diagnosis (quarters)	15.4	15.4	0.0	0.000
Age at diagnosis	67.59	66.12	1.46	0.129
Female (%)	44.20	46.79	-2.59	-0.068
University (%)	2.85	3.16	-0.31	-0.027
Austrian (%)	91.84	88.99	2.85	0.147
Charlson index (%)	24.17	21.89	2.28	0.059
Panel B: Spending (EUR)				
Healthcare spending	45,329	9,365	35,963	

Notes: This table presents covariate balance and excess last year of life spending. The last year of life is defined as the last four quarters before death. Panel a) shows balance on key covariates between matched decedents and survivors. Survivors are reweighted to match the decedent distribution across 730 bins defined by predicted mortality risk (50 bins) and disease (18 diseases). SMD denotes the standardized mean difference, calculated as the difference in means divided by the pooled standard deviation; values below 0.10 indicate good balance. Panel b) reports healthcare spending in the last year of life, including observed spending for decedents, counterfactual spending constructed from matched survivors evaluated at the same point in the disease trajectory, and excess spending defined as the difference between observed and counterfactual spending.

Table B.6 — Event study estimates on labor market outcomes, treatment intensity

	Employment (1)	Sick Leave (2)	Unemployment (3)	Retirement (4)	Out of LF (5)
t=-16	0.0165	-0.0251	0.0049	-0.0006	-0.0001
t=-15	0.0147	-0.0252	0.0099	-0.0043	-0.0001
t=-14	0.0198	-0.0191	0.0020	-0.0044	-0.0001
t=-13	0.0119	-0.0189	0.0093	-0.0027	-0.0002
t=-12	0.0109	-0.0200	0.0113	-0.0009	-0.0002
t=-11	-0.0006	-0.0213	0.0142	0.0078	-0.0001
t=-10	0.0076	-0.0162	0.0058	0.0044	-0.0001
t=-9	0.0092	-0.0231	-0.0013	0.0057	-0.0001
t=-8	0.0110	-0.0169	-0.0055	0.0048	-0.0001
t=-7	0.0083	-0.0211	0.0043	0.0046	-0.0001
t=-6	-0.0032	0.0118	0.0003	0.0021	-0.0001
t=-5	-0.0042	-0.0055	0.0018	-0.0003	0.0000
t=-3	0.0007	-0.0219	0.0082	0.0014	-0.0000
t=-2	-0.0003	-0.0263	0.0060	0.0045	-0.0000
t=-1	0.0009	-0.0278	0.0071	0.0019	-0.0001
t=0	0.0029	-0.0174	0.0095	-0.0029	-0.0001
t=1	-0.0026	-0.0155	0.0156	-0.0044	-0.0000
t=2	-0.0001	-0.0217	0.0134	-0.0078	-0.0001
t=3	0.0094	-0.0265	0.0095	-0.0116	-0.0002
t=4	0.0153	-0.0224	0.0065	-0.0123	-0.0001
t=5	0.0127	-0.0087	0.0025	-0.0130	-0.0001
t=6	0.0124	-0.0103	0.0007	-0.0167	-0.0001
t=7	0.0197	-0.0131	0.0040	-0.0187	-0.0001
t=8	0.0190	-0.0180	0.0044	-0.0182	-0.0001
t=9	0.0134	-0.0228	0.0060	-0.0154	-0.0002
t=10	0.0140	-0.0212	0.0052	-0.0159	-0.0001
t=11	0.0107	-0.0163	0.0021	-0.0128	-0.0002
t=12	0.0071	-0.0192	0.0037	-0.0029	-0.0001
t=13	0.0063	-0.0188	0.0016	0.0026	-0.0001
t=14	-0.0031	-0.0181	-0.0037	0.0082	-0.0002
t=15	-0.0047	-0.0195	-0.0015	0.0055	-0.0001
t=16	0.0011	-0.0194	-0.0000	0.0018	-0.0001
Observations	114,447	114,447	114,447	114,447	114,447
Mean outcome (t=-4)	32.1019	1.6382	2.2037	34.7000	0.2183
Effect t=-2 (%)	0.00	-1.60	0.27	0.01	-0.02
Effect t=0 (%)	0.01	-1.06	0.43	-0.01	-0.03
Effect t=8 (%)	0.06	-1.10	0.20	-0.05	-0.06
Effect t=16 (%)	0.00	-1.18	0.00	0.01	-0.05
Disease FE	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes
Spouse age FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes

Notes: The table displays the estimated effects of end-of-life medical spending on surviving spouses' labor market outcomes from Equation (5). All labor market outcomes are measured in days, with zero assigned when an individual is not in the respective labor market state. Coefficients are interpreted as effects per additional 1,000 € of excess end-of-life medical spending. Estimates are measured relative to the baseline of four quarters before death ($k = -4$). Data on labor market outcomes are from the Austrian Social Security Database and cover the period 2006–2018. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.7 — Event study estimates on healthcare utilization, treatment intensity

	Physician Visit (1)	Drug Use (2)	Hospital Admission (3)	Mental Health Care (4)
t=-16	0.0002	-0.0001	0.0001	-0.0001
t=-15	0.0002	-0.0000	0.0001	-0.0000
t=-14	-0.0000	-0.0001	-0.0001	-0.0001
t=-13	0.0000	0.0003	-0.0000	-0.0001
t=-12	0.0000	0.0004	-0.0001	0.0001
t=-11	0.0001	0.0000	-0.0001	-0.0000
t=-10	-0.0002	-0.0003	-0.0001	-0.0001
t=-9	0.0002	0.0004	-0.0001	-0.0001
t=-8	0.0000	-0.0001	0.0000	-0.0000
t=-7	0.0001	0.0001	0.0002	-0.0001
t=-6	0.0002	0.0003	0.0001	0.0001
t=-5	0.0000	0.0003	0.0004	-0.0001
t=-3	-0.0004	-0.0001	-0.0001	-0.0002
t=-2	-0.0002	-0.0002	-0.0001	-0.0001
t=-1	-0.0002	-0.0000	0.0001	0.0000
t=0	-0.0004	0.0001	0.0005*	0.0003
t=1	-0.0003	-0.0003	0.0004	0.0000
t=2	0.0000	0.0001	0.0001	-0.0001
t=3	-0.0003	-0.0001	0.0002	-0.0002
t=4	-0.0002	-0.0002	-0.0001	-0.0001
t=5	-0.0004	-0.0003	-0.0001	-0.0000
t=6	0.0000	0.0000	0.0000	-0.0002
t=7	-0.0003	-0.0001	-0.0001	-0.0001
t=8	-0.0002	-0.0002	0.0002	-0.0001
t=9	-0.0001	-0.0001	-0.0001	-0.0002
t=10	-0.0003	-0.0003	0.0000	-0.0001
t=11	-0.0004	-0.0002	-0.0001	-0.0002
t=12	-0.0002	-0.0000	0.0001	-0.0000
t=13	-0.0002	-0.0001	0.0003	-0.0002
t=14	-0.0005	-0.0005	0.0001	-0.0001
t=15	-0.0001	-0.0002	0.0001	-0.0001
t=16	-0.0004	-0.0002	0.0002	-0.0002
Observations	33,297	33,297	33,297	33,297
Mean outcome (t=-4)	0.4658	0.3523	0.0328	0.0598
Effect t=-2 (%)	-0.04	-0.06	-0.37	-0.11
Effect t=0 (%)	-0.08	0.02	1.44	0.53
Effect t=8 (%)	-0.05	-0.04	0.58	-0.18
Effect t=16 (%)	-0.08	-0.07	0.64	-0.27
Disease FE	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes
Spouse age FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes

Notes: The table displays the estimated effects of end-of-life medical spending on surviving spouses' healthcare utilization from Equation (5). Healthcare utilization is measured using indicator variables (0/1). Coefficients are interpreted as effects per additional 1,000 € of excess end-of-life medical spending. Estimates are measured relative to the baseline of four quarters before death ($k = -4$). Data on health outcomes are from the Upper Austrian Health Insurance Fund and cover the period 2006–2018. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.8 — Event study estimates on labor market outcomes, by type of service

	Employment (1)	Sick Leave (2)	Unemployment (3)	Retirement (4)	Out of LF (5)
a) Outpatient Expenditure					
Pre-trends (F-stat)	0.09	1.04	1.28	0.16	0.02
Joint post-LYOL (F-stat)	0.38	0.61	0.42	0.22	0.07
Average post-LYOL	0.000	-0.000	0.000	-0.000	-0.000
Static post-LYOL	0.000*	-0.000	-0.000*	0.000	-0.000**
b) Inpatient Expenditure					
Pre-trends (F-stat)	0.23	1.28	0.54	0.14	0.10
Joint post-LYOL (F-stat)	0.33	1.15	0.88	0.44	0.08
Average post-LYOL	0.000	-0.000	0.000	-0.000	-0.000
Static post-LYOL	0.000	-0.000	0.000	-0.000**	-0.000
c) Drug Expenditure					
Pre-trends (F-stat)	0.45	1.19	0.48	0.03	0.18
Joint post-LYOL (F-stat)	0.27	0.58	0.36	0.17	0.59
Average post-LYOL	-0.000	-0.000	0.000	0.000	-0.000
Static post-LYOL	-0.000**	-0.000	-0.000	0.000	-0.000

Notes: The table displays the estimated effects of end-of-life medical spending on surviving spouses' labor market outcomes. Estimates are reported by type of service across panels a)–c) (inpatient, outpatient, and prescription drug services). Each panel reports (i) a joint F-test for pre-trends ($k \leq -4$); (ii) a joint F-test for the post-LYOL event-study coefficients ($k > -4$) from Equation (5); (iii) the average post-LYOL effect from Equation (5); and (iv) the average static effect estimated by regressing outcomes on an indicator for the post-LYOL period ($k > -4$). All labor market outcomes are measured in days, with zero assigned when an individual is not in the respective labor market state. Data on labor market outcomes are from the Austrian Social Security Database and cover the period 2006–2018. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.9 — Event study estimates on healthcare utilization, by type of service

	Physician Visits (1)	Drug Use (2)	Hospital Admission (3)	Mental Health Care (4)
a) Outpatient Expenditure				
Pre-trends (F-stat)	0.12	0.14	1.15	0.31
Joint post-LYOL (F-stat)	0.17	0.19	0.49	0.13
Average post-LYOL	0.000	0.000	0.000	-0.000
Static post-LYOL	0.000	0.000**	0.000	0.000
b) Inpatient Expenditure				
Pre-trends (F-stat)	0.22	0.73	1.15	0.24
Joint post-LYOL (F-stat)	0.42	0.28	1.11	0.38
Average post-LYOL	-0.000	-0.000	-0.000	-0.000
Static post-LYOL	-0.000***	-0.000*	0.000	-0.000
c) Drug Expenditure				
Pre-trends (F-stat)	0.07	0.17	3.83***	0.08
Joint post-LYOL (F-stat)	1.32	0.17	13.20***	0.11
Average post-LYOL	-0.000	-0.000	0.000***	-0.000
Static post-LYOL	-0.000**	-0.000**	0.000	0.000

Notes: The table displays the estimated effects of end-of-life medical spending on surviving spouses' healthcare utilization. Estimates are reported by type of service across panels a)–c) (inpatient, outpatient, and prescription drug services). Each panel reports (i) a joint F-test for pre-trends ($k \leq -4$); (ii) a joint F-test for the post-LYOL event-study coefficients ($k > -4$) from Equation (5); (iii) the average post-LYOL effect from Equation (5); and (iv) the average static effect estimated by regressing outcomes on an indicator for the post-LYOL period ($k > -4$). Healthcare utilization is measured using indicator variables (0/1). Data on health outcomes are from the Upper Austrian Health Insurance Fund and cover the period 2006–2018. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE B.10 — Event study estimates on labor market outcomes, across the excess spending distribution

	Employment (1)	Sick Leave (2)	Unemployment (3)	Retirement (4)	Out of LF (5)
a) Very Low Intensity (Q1)					
Pre-trends (F-stat)	0.08	0.71	0.64	0.08	0.03
Joint post-LYOL (F-stat)	0.30	1.09	0.42	0.29	0.15
Average post-LYOL	0.000	-0.000	0.000	-0.000	0.000
Static post-LYOL	0.000**	0.000	0.000**	-0.000***	0.000*
b) Low Intensity (Q2)					
Pre-trends (F-stat)	0.19	0.70	0.10	0.06	0.04
Joint post-LYOL (F-stat)	0.16	0.80	0.51	0.21	0.10
Average post-LYOL	0.000	-0.000	-0.000	0.000	0.000
Static post-LYOL	-0.000	-0.000	-0.000*	0.000	0.000
c) Medium Intensity (Q3)					
Pre-trends (F-stat)	0.09	0.72	0.27	0.13	0.18
Joint post-LYOL (F-stat)	0.38	0.77	0.34	0.07	0.04
Average post-LYOL	-0.000	-0.000	-0.000	0.000	0.000
Static post-LYOL	-0.000	0.000	-0.000	0.000	-0.000
d) High Intensity (Q4)					
Pre-trends (F-stat)	0.14	1.18	0.34	0.20	0.05
Joint post-LYOL (F-stat)	0.13	0.99	0.39	0.09	0.07
Average post-LYOL	-0.000	0.000	-0.000	-0.000	-0.000
Static post-LYOL	0.000	-0.000	-0.000	-0.000***	0.000
e) Very High Intensity (Q5)					
Pre-trends (F-stat)	0.38	0.82	0.49	0.24	0.13
Joint post-LYOL (F-stat)	0.66	0.60	2.03***	0.23	0.13
Average post-LYOL	0.000	-0.000	-0.000	-0.000	-0.000
Static post-LYOL	0.000*	-0.000	-0.000	-0.000	-0.000

Notes: The table displays the estimated effects of end-of-life medical spending on surviving spouses' labor market outcomes. Estimates are reported by quintiles of the excess spending distribution across panels a)–e) (Q1–Q5). Each panel reports (i) a joint F-test for pre-trends ($k \leq -4$); (ii) a joint F-test for the post-LYOL event-study coefficients ($k > -4$) from Equation (5); (iii) the average post-LYOL effect from Equation (5); and (iv) the average static effect estimated by regressing outcomes on an indicator for the post-LYOL period ($k > -4$). All labor market outcomes are measured in days, with zero assigned when an individual is not in the respective labor market state. Data on labor market outcomes are from the Austrian Social Security Database and cover the period 2006–2018. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.11 — Event study estimates on healthcare utilization, across the excess spending distribution

	Physician Visits (1)	Drug Use (2)	Hospital Admission (3)	Mental Health Care (4)
a) Very Low Intensity (Q1)				
Pre-trends (F-stat)	0.57	0.67	0.72	0.40
Joint post-LYOL (F-stat)	0.27	0.59	0.76	0.49
Average post-LYOL	0.000	0.000	0.000	-0.000
Static post-LYOL	0.000	-0.000	0.000	-0.000**
b) Low Intensity (Q2)				
Pre-trends (F-stat)	0.17	0.37	0.81	0.47
Joint post-LYOL (F-stat)	0.24	0.40	0.74	0.38
Average post-LYOL	0.000	0.000	-0.000	0.000
Static post-LYOL	-0.000	0.000	-0.000	-0.000*
c) Medium Intensity (Q3)				
Pre-trends (F-stat)	0.27	0.19	0.86	0.37
Joint post-LYOL (F-stat)	0.12	0.30	0.58	0.37
Average post-LYOL	-0.000	-0.000	-0.000	-0.000
Static post-LYOL	0.000	-0.000	0.000	0.000
d) High Intensity (Q4)				
Pre-trends (F-stat)	0.13	0.65	1.30	0.24
Joint post-LYOL (F-stat)	0.13	0.19	1.31	0.21
Average post-LYOL	0.000	-0.000	-0.000*	-0.000
Static post-LYOL	-0.000	0.000	-0.000	0.000*
e) Very High Intensity (Q5)				
Pre-trends (F-stat)	0.39	0.79	0.78	0.08
Joint post-LYOL (F-stat)	0.53	0.39	0.61	0.45
Average post-LYOL	-0.000	-0.000	0.000	-0.000
Static post-LYOL	-0.000	0.000	0.000	-0.000***

Notes: The table displays the estimated effects of end-of-life medical spending on surviving spouses' healthcare utilization. Estimates are reported by quintiles of the excess spending distribution across panels a)–e) (Q1–Q5). Each panel reports (i) a joint F-test for pre-trends ($k \leq -4$); (ii) a joint F-test for the post-LYOL event-study coefficients ($k > -4$) from Equation (5); (iii) the average post-LYOL effect from Equation (5); and (iv) the average static effect estimated by regressing outcomes on an indicator for the post-LYOL period ($k > -4$). Healthcare utilization is measured using indicator variables (0/1). Data on health outcomes are from the Upper Austrian Health Insurance Fund and cover the period 2006–2018. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. .

Table B.12 — Event study estimates on labor market outcomes, by gender

	Employment		Sick Leave		Unemployment		Retirement		Out of LF	
	Baseline (1)	Interaction (2)	Baseline (3)	Interaction (4)	Baseline (5)	Interaction (6)	Baseline (7)	Interaction (8)	Baseline (9)	Interaction (10)
Panel A: Female										
t=-2	-0.7637	-0.0003	0.0114	-0.0364	-0.0659	0.0111	0.3659	0.0044	0.0032	-0.0001
t=0	-2.9053***	0.0055	0.7553**	-0.0259	0.1209	0.0139	0.3685	-0.0003	0.0083	-0.0001
t=4	-2.5561***	0.0146	0.7169	-0.0334	-0.1861	0.0104	-0.1750	-0.0061	0.0213**	-0.0002
t=8	-2.7019***	0.0185	-0.4434	-0.0311	-0.5005*	0.0076	-0.2244	-0.0137	0.0304***	-0.0002
t=12	-2.9213***	0.0058	-0.4544	-0.0307	-0.7413***	0.0038	-0.3135	0.0042	0.0369***	-0.0001
t=16	-3.1111***	0.0014	-0.6306**	-0.0299	-0.5597**	0.0063	-0.1936	0.0118	0.0328***	-0.0002
Pre-trends (F-stat)	0.19	0.33	0.60	1.12	0.27	0.54	0.10	0.26	0.08	0.22
Observations	133,552	72,254	133,552	72,254	133,552	72,254	133,552	72,254	133,552	72,254
Mean outcome (t=-4)	32.4160	32.4160	2.0113	2.0113	2.5099	2.5099	36.1565	36.1565	0.2072	0.2072
Disease FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spouse age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Male										
t=-2	-0.2377	0.0012	0.2239	-0.0017	0.1215	-0.0067	-0.2081	0.0044	0.0017	0.0000
t=0	-1.3462	-0.0044	0.3399	0.0048	0.1498	-0.0011	-0.2210	-0.0124	0.0039	0.0001
t=4	-0.6518	0.0126	-0.1068	0.0053	0.0461	-0.0042	-0.2928	-0.0249	0.0044	0.0001
t=8	-1.3710	0.0125	0.2154	0.0129	0.1733	-0.0031	0.0691	-0.0200	0.0044	-0.0001
t=12	-1.2444	0.0081	-0.4913***	0.0087**	-0.0573	0.0034	-0.4153	-0.0190	0.0066	-0.0000
t=16	-1.1149	0.0028	-0.1856	0.0057	0.0055	-0.0170	-0.5824	-0.0273	0.0057	-0.0000
Pre-trends (F-stat)	0.04	0.28	0.85	1.30	0.47	0.42	0.09	0.02	0.04	0.07
Observations	74,072	42,193	74,072	42,193	74,072	42,193	74,072	42,193	74,072	42,193
Mean outcome (t=-4)	31.5366	31.5366	0.9667	0.9667	1.6528	1.6528	32.0789	32.0789	0.2381	0.2381
Disease FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spouse age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table displays the estimated effects of end-of-life medical spending on surviving spouses' labor market outcomes from Equation (1) (baseline) and Equation (5) (interaction). Equations are estimated separately by gender. All labor market outcomes are measured in days, with zero assigned when an individual is not in the respective labor market state. Interaction coefficients are interpreted as effects per additional 1,000 € of excess end-of-life medical spending. Estimates are measured relative to the baseline of four quarters before death ($k = -4$). Data on labor market outcomes are from the Austrian Social Security Database and cover the period 2006–2018. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.13 — Event study estimates on labor market outcomes, by age group

	Employment		Sick Leave		Unemployment		Retirement		Out of LF	
	Baseline (1)	Interaction (2)	Baseline (3)	Interaction (4)	Baseline (5)	Interaction (6)	Baseline (7)	Interaction (8)	Baseline (9)	Interaction (10)
Panel A: Below median age										
t=-2	-0.8369	0.0029	0.0103	-0.0451	-0.0689	0.0103	0.4283	0.0028	0.0033	-0.0000
t=0	-3.9009***	0.0058	1.0334**	-0.0292	0.2487	0.0152	0.6304	-0.0036	0.0104	-0.0001
t=4	-2.5950**	0.0228	0.6120	-0.0387	-0.2432	0.0081	0.0936	-0.0144	0.0238**	-0.0002
t=8	-2.9371***	0.0243	-0.6911	-0.0306	-0.6474	0.0046	0.0601	-0.0238	0.0359***	-0.0002
t=12	-3.0707***	0.0029	-1.2816***	-0.0320	-1.1700***	0.0031	-0.2686	-0.0029	0.0455***	-0.0001
t=16	-3.0491***	-0.0061	-1.3412***	-0.0327	-0.9704**	-0.0030	-0.3124	0.0098	0.0370***	-0.0001
Pre-trends (F-stat)	0.28	0.21	0.70	1.05	0.35	0.76	2.33***	0.18	0.11	0.40
Observations	103,625	54,642	103,625	54,642	103,625	54,642	103,625	54,642	103,625	54,642
Mean outcome (t=-4)	56.3546	56.3546	3.2104	3.2104	3.9542	3.9542	8.3616	8.3616	0.1710	0.1710
Disease FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spouse age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Above median age										
t=-2	-0.4254	-0.0047	0.1688**	0.0005	0.0558	0.0001	0.1505	0.0073	0.0007	-0.0001
t=0	-1.0548*	-0.0009	0.1619***	-0.0007	0.0010	0.0013	0.2331	-0.0000	0.0003	-0.0000
t=4	-1.4495***	0.0051	0.0948**	0.0003	-0.0212	0.0040	0.2968	-0.0062	0.0027	-0.0001
t=8	-1.9061***	0.0098	0.0741**	0.0004	-0.0351	0.0040	0.7316	-0.0058	0.0025	-0.0001
t=12	-1.8438***	0.0102	0.0718**	0.0004	-0.0413	0.0039	0.6061	0.0015	0.0019	-0.0001
t=16	-1.9171***	0.0095	0.0715**	0.0004	-0.0135	0.0040	0.7474	-0.0056	0.0027	-0.0001
Pre-trends (F-stat)	0.45	0.26	0.86	0.98	0.28	0.43	0.19	0.17	0.09	0.03
Observations	103,999	59,805	103,999	59,805	103,999	59,805	103,999	59,805	103,999	59,805
Mean outcome (t=-4)	7.9946	7.9946	0.0755	0.0755	0.4637	0.4637	60.8803	60.8803	0.2653	0.2653
Disease FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spouse age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table displays the estimated effects of end-of-life medical spending on surviving spouses' labor market outcomes from Equation (1) (baseline) and Equation (5) (interaction). Equations are estimated separately by age group; the median age at death is 61. All labor market outcomes are measured in days, with zero assigned when an individual is not in the respective labor market state. Interaction coefficients are interpreted as effects per additional 1,000 € of excess end-of-life medical spending. Estimates are measured relative to the baseline of four quarters before death ($k = -4$). Data on labor market outcomes are from the Austrian Social Security Database and cover the period 2006–2018. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.14 — Event study estimates on labor market outcomes, by university degree

	Employment		Sick Leave		Unemployment		Retirement		Out of LF	
	Baseline (1)	Interaction (2)	Baseline (3)	Interaction (4)	Baseline (5)	Interaction (6)	Baseline (7)	Interaction (8)	Baseline (9)	Interaction (10)
Panel A: No university degree										
t=-2	-0.5780	-0.0005	0.0837	-0.0271	0.0038	0.0059	0.2281	0.0049	0.0019	-0.0000
t=0	-2.3161***	0.0021	0.6069**	-0.0178	0.1141	0.0100	0.2528	-0.0025	0.0054	-0.0001
t=4	-1.8608***	0.0141	0.4475	-0.0229	-0.1192	0.0064	-0.1143	-0.0116	0.0136*	-0.0001
t=8	-2.2936***	0.0186	-0.1905	-0.0184	-0.3283	0.0050	0.1500	-0.0170	0.0191**	-0.0001
t=12	-2.3699***	0.0057	-0.4562*	-0.0197	-0.5761***	0.0042	0.0257	-0.0008	0.0233***	-0.0001
t=16	-2.4968***	-0.0003	-0.4716**	-0.0200	-0.4269**	0.0002	0.1238	0.0048	0.0193**	-0.0001
Pre-trends (F-stat)	0.18	0.29	0.45	1.04	0.38	0.60	0.04	0.11	0.12	0.17
Observations	199,101	109,385	199,101	109,385	199,101	109,385	199,101	109,385	199,101	109,385
Mean outcome (t=-4)	31.4643	31.4643	1.6974	1.6974	2.2574	2.2574	35.4011	35.4011	0.2205	0.2205
Disease FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spouse age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: University degree										
t=-2	-0.0963	0.0007	0.3337	0.0119	-0.3040	0.0109	-1.2088	0.0083	0.0105	-0.0002
t=0	-2.4394	0.0438	0.8848*	0.0076	0.6341	-0.0127	-1.6935	0.0251	0.0204	-0.0006
t=4	-1.6870	0.0625	0.2377	0.0041	0.4131	0.0142	-1.5180	-0.0040	0.0250	-0.0010
t=8	-0.3611	0.0218	-0.3318**	0.0028	1.1346	-0.0195	-3.5733	-0.0320	0.0251	-0.0006
t=12	0.0256	0.0464	-0.3318*	0.0084	1.0839	-0.0181	-5.7494**	-0.0315	0.0361	-0.0002
t=16	1.7198	0.0512	-0.2505	0.0036	1.0123	-0.0078	-7.9699***	-0.1004	0.0472	-0.0003
Pre-trends (F-stat)	0.30	0.07	1.07	0.62	0.51	0.48	0.17	0.17	0.19	0.08
Observations	8,523	5,062	8,523	5,062	8,523	5,062	8,523	5,062	8,523	5,062
Mean outcome (t=-4)	47.0039	47.0039	0.2548	0.2548	0.9498	0.9498	18.3127	18.3127	0.1660	0.1660
Disease FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spouse age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table displays the estimated effects of end-of-life medical spending on surviving spouses' labor market outcomes from Equation (1) (baseline) and Equation (5) (interaction). Equations are estimated separately by educational attainment. All labor market outcomes are measured in days, with zero assigned when an individual is not in the respective labor market state. Interaction coefficients are interpreted as effects per additional 1,000€ of excess end-of-life medical spending. Estimates are measured relative to the baseline of four quarters before death ($k = -4$). Data on labor market outcomes are from the Austrian Social Security Database and cover the period 2006–2018. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.15 — Event study estimates on healthcare utilization, by gender

	Physician Visits		Drug Use		Hospital Admission		Mental Health Care	
	Baseline	Interaction	Baseline	Interaction	Baseline	Interaction	Baseline	Interaction
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Female								
t=-2	-0.0054	-0.0003	0.0109	-0.0003	-0.0058	-0.0001	0.0167	-0.0001
t=0	0.0201	-0.0006	0.0361**	-0.0000	-0.0047	0.0005*	0.0633***	0.0004
t=4	-0.0115	-0.0003	0.0039	-0.0003	0.0162*	-0.0001	0.0467***	-0.0001
t=8	-0.0227	-0.0004	-0.0044	-0.0002	0.0109	0.0003	0.0389***	-0.0002
t=12	-0.0278	-0.0004	-0.0160	-0.0001	0.0004	0.0001	0.0417***	-0.0001
t=16	-0.0306*	-0.0006	-0.0231	-0.0004	0.0002	0.0002	0.0509***	-0.0002
Pre-trends (F-stat)	0.81	0.22	1.21	0.66	1.39	1.17	0.41	0.08
Observations	48,840	23,034	48,840	23,034	48,840	23,034	48,840	23,034
Mean outcome (t=-4)	0.6095	0.6095	0.4622	0.4622	0.0446	0.0446	0.0824	0.0824
Disease FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spouse age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Male								
t=-2	-0.0003	0.0003	-0.0031	0.0004	0.0010	-0.0001	0.0036	-0.0001
t=0	-0.0076	0.0004	-0.0037	0.0005	0.0071	0.0001	0.0094	0.0001
t=4	-0.0246	0.0004	-0.0280*	0.0003	0.0040	-0.0002	0.0043	0.0002
t=8	-0.0357*	0.0003	-0.0357**	0.0000	-0.0025	-0.0001	-0.0005	0.0001
t=12	-0.0500***	0.0003	-0.0512***	0.0004	-0.0001	0.0003	0.0017	0.0002
t=16	-0.0364*	0.0004	-0.0374**	0.0003	-0.0010	0.0003	-0.0021	-0.0000
Pre-trends (F-stat)	1.29	0.11	1.02	0.50	0.97	0.78	0.51	0.43
Observations	20,658	10,263	20,658	10,263	20,658	10,263	20,658	10,263
Mean outcome (t=-4)	0.1262	0.1262	0.0927	0.0927	0.0048	0.0048	0.0064	0.0064
Disease FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spouse age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table displays the estimated effects of end-of-life medical spending on surviving spouses' healthcare utilization from Equation (1) (baseline) and Equation (5) (interaction). Equations are estimated separately by gender. Healthcare utilization is measured using indicator variables (0/1). Interaction coefficients are interpreted as effects per additional 1,000 € of excess end-of-life medical spending. Estimates are measured relative to the baseline of four quarters before death ($k = -4$). Data on health outcomes are from the Upper Austrian Health Insurance Fund and cover the period 2006–2018. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.16 — Event study estimates on healthcare utilization, by age group

	Physician Visits		Drug Use		Hospital Admission		Mental Health Care	
	Baseline (1)	Interaction (2)	Baseline (3)	Interaction (4)	Baseline (5)	Interaction (6)	Baseline (7)	Interaction (8)
Panel A: Below median age								
t=-2	-0.0127	-0.0001	0.0095	-0.0002	-0.0051	-0.0001	0.0132	-0.0001
t=0	0.0079	-0.0003	0.0236	0.0001	-0.0007	0.0005*	0.0571***	0.0002
t=4	-0.0313	-0.0002	-0.0176	-0.0004	0.0163*	-0.0003*	0.0352***	-0.0001
t=8	-0.0474**	-0.0002	-0.0291	-0.0003	0.0038	0.0004	0.0225**	-0.0001
t=12	-0.0650***	-0.0000	-0.0611***	0.0000	-0.0067	0.0001	0.0228**	0.0000
t=16	-0.0696***	-0.0003	-0.0672***	-0.0003	-0.0036	0.0003	0.0235**	-0.0001
Pre-trends (F-stat)	1.43	0.28	1.68*	0.75	2.06**	0.80	0.25	0.12
Observations	41,844	19,668	41,844	19,668	41,844	19,668	41,844	19,668
Mean outcome (t=-4)	0.5505	0.5505	0.3920	0.3920	0.0363	0.0363	0.0718	0.0718
Disease FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spouse age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Above median age								
t=-2	0.0052	-0.0003	0.0002	-0.0002	-0.0014	-0.0002	0.0113	0.0000
t=0	0.0141	-0.0004	0.0230	0.0001	-0.0009	0.0003	0.0310***	0.0007
t=4	0.0001	-0.0002	0.0043	0.0002	0.0063	0.0004	0.0295***	0.0001
t=8	-0.0104	-0.0003	-0.0056	0.0005	0.0105	-0.0002	0.0284**	-0.0001
t=12	-0.0110	-0.0003	0.0030	0.0001	0.0067	0.0001	0.0325***	-0.0001
t=16	-0.0116	-0.0001	-0.0062	0.0003	-0.0008	-0.0001	0.0403***	-0.0003
Pre-trends (F-stat)	0.47	0.17	0.41	0.25	0.32	1.14	0.73	0.07
Observations	27,654	13,629	27,654	13,629	27,654	13,629	27,654	13,629
Mean outcome (t=-4)	0.3377	0.3377	0.2924	0.2924	0.0274	0.0274	0.0418	0.0418
Disease FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spouse age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table displays the estimated effects of end-of-life medical spending on surviving spouses' healthcare utilization from Equation (1) (baseline) and Equation (5) (interaction). Equations are estimated separately by age group; the median age at death is 61. Healthcare utilization is measured using indicator variables (0/1). Interaction coefficients are interpreted as effects per additional 1,000 € of excess end-of-life medical spending. Estimates are measured relative to the baseline of four quarters before death ($k = -4$). Data on health outcomes are from the Upper Austrian Health Insurance Fund and cover the period 2006–2018. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.17 — Event study estimates on healthcare utilization, by university degree

	Physician Visits		Drug Use		Hospital Admission		Mental Health Care	
	Baseline (1)	Interaction (2)	Baseline (3)	Interaction (4)	Baseline (5)	Interaction (6)	Baseline (7)	Interaction (8)
Panel A: No university degree								
t=-2	-0.0042	-0.0002	0.0072	-0.0002	-0.0046	-0.0001	0.0123	-0.0001
t=0	0.0133	-0.0004	0.0274*	0.0001	-0.0007	0.0005*	0.0492***	0.0003
t=4	-0.0118	-0.0002	-0.0001	-0.0003	0.0136**	-0.0001	0.0364***	-0.0001
t=8	-0.0224	-0.0003	-0.0086	-0.0002	0.0076	0.0002	0.0293***	-0.0001
t=12	-0.0249*	-0.0002	-0.0197	-0.0001	0.0014	0.0001	0.0313***	-0.0000
t=16	-0.0253*	-0.0004	-0.0197	-0.0002	0.0002	0.0002	0.0362***	-0.0002
Pre-trends (F-stat)	1.02	0.18	1.39	0.53	1.39	1.05	0.45	0.09
Observations	67,386	32,208	67,386	32,208	67,386	32,208	67,386	32,208
Mean outcome (t=-4)	0.4682	0.4682	0.3550	0.3550	0.0333	0.0333	0.0607	0.0607
Disease FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spouse age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: University degree								
t=-2	-0.0166	0.0024	-0.0092	-0.0013	0.0139	0.0012	0.0296	-0.0006
t=0	-0.0239	0.0037	-0.0465	0.0001	-0.0197	-0.0017	0.0009	-0.0009
t=4	-0.1303*	0.0061*	-0.1568***	0.0003	-0.0163	-0.0016	-0.0113	-0.0010
t=8	-0.1645**	0.0003	-0.1708**	0.0017	0.0016	-0.0017	-0.0073	-0.0013
t=12	-0.3549***	0.0033	-0.2380***	-0.0002	-0.0332	-0.0017	0.0155	0.0003
t=16	-0.2861***	0.0045	-0.3090***	-0.0008	-0.0175	-0.0045*	0.0319	-0.0009
Pre-trends (F-stat)	0.74	0.34	0.70	0.44	1.31	0.68	1.75*	0.46
Observations	2,112	1,089	2,112	1,089	2,112	1,089	2,112	1,089
Mean outcome (t=-4)	0.3906	0.3906	0.2656	0.2656	0.0156	0.0156	0.0312	0.0312
Disease FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spouse age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table displays the estimated effects of end-of-life medical spending on surviving spouses' healthcare utilization from Equation (1) (baseline) and Equation (5) (interaction). Equations are estimated separately by educational attainment. Healthcare utilization is measured using indicator variables (0/1). Interaction coefficients are interpreted as effects per additional 1,000 € of excess end-of-life medical spending. Estimates are measured relative to the baseline of four quarters before death ($k = -4$). Data on health outcomes are from the Upper Austrian Health Insurance Fund and cover the period 2006–2018. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE B.18 — Event study estimates on labor market outcomes, alternative treatment intensity measures

	Employment (1)	Sick Leave (2)	Unemployment (3)	Retirement (4)	Out of LF (5)
a) Total LYOL Spending (Baseline Measure)					
Pre-trends (F-stat)	0.31	1.07	0.62	0.14	0.18
Joint post-LYOL (F-stat)	0.35	1.26	0.77	0.57	0.15
Average post-LYOL	0.007	-0.019	0.005	-0.006	-0.000
Static post-LYOL	-0.001	-0.004	0.001	-0.008*	-0.000
b) Mean LYOL Spending (Quarter-Adjusted)					
Pre-trends (F-stat)	0.24	0.99	0.51	0.14	0.13
Joint post-LYOL (F-stat)	0.34	1.35	1.18	0.52	0.14
Average post-LYOL	0.038	-0.076	0.005	-0.022	-0.000
Static post-LYOL	0.002	-0.016	0.001	-0.029*	-0.000
c) Mean Spending from Diagnosis to Death					
Pre-trends (F-stat)	0.18	0.67	0.29	0.15	0.05
Joint post-LYOL (F-stat)	0.59	0.92	1.15	0.32	0.09
Average post-LYOL	0.018	-0.029	-0.001	0.008	-0.000
Static post-LYOL	0.003	0.006	0.013**	-0.008	-0.000
d) Simple Counterfactual					
Pre-trends (F-stat)	0.33	0.91	0.75	0.20	0.16
Joint post-LYOL (F-stat)	0.41	1.17	0.78	0.59	0.16
Average post-LYOL	0.000	-0.000	0.000	-0.000	-0.000
Static post-LYOL	0.000	-0.000	0.000	-0.000	-0.000
e) Regression-Based Counterfactual					
Pre-trends (F-stat)	0.34	0.87	0.71	0.21	0.16
Joint post-LYOL (F-stat)	0.41	1.20	0.71	0.57	0.18
Average post-LYOL	0.000	-0.000	0.000	-0.000	-0.000
Static post-LYOL	0.000	-0.000	0.000	-0.000	-0.000

Notes: The table displays the estimated effects of end-of-life medical spending on surviving spouses' labor market outcomes. Estimates are reported for three measures of treatment intensity and two alternative constructions of the counterfactual, across panels a)–e). Each panel reports (i) a joint F-test for pre-trends ($k \leq -4$); (ii) a joint F-test for the post-LYOL event-study coefficients ($k > -4$) from Equation (5); (iii) the average post-LYOL effect from Equation (5); and (iv) the average static effect estimated by regressing outcomes on an indicator for the post-LYOL period ($k > -4$). All labor market outcomes are measured in days, with zero assigned when an individual is not in the respective labor market state. Data on labor market outcomes are from the Austrian Social Security Database and cover the period 2006–2018. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.19 — Event study estimates on healthcare utilization, alternative treatment intensity measures

	Physician Visits (1)	Drug Use (2)	Hospital Admission (3)	Mental Health Care (4)
a) Total LYOL Spending (Baseline Measure)				
Pre-trends (F-stat)	0.20	0.54	1.04	0.09
Joint post-LYOL (F-stat)	0.32	0.24	1.22	0.18
Average post-LYOL	-0.000	-0.000	0.000	-0.000
Static post-LYOL	-0.000***	-0.000**	0.000	-0.000
b) Mean LYOL Spending (Quarter-Adjusted)				
Pre-trends (F-stat)	0.26	0.47	0.93	0.09
Joint post-LYOL (F-stat)	0.35	0.28	1.17	0.20
Average post-LYOL	-0.001	-0.001	0.000	-0.000
Static post-LYOL	-0.001***	-0.001***	0.000	-0.000
c) Mean Spending from Diagnosis to Death				
Pre-trends (F-stat)	0.10	0.23	1.10	0.13
Joint post-LYOL (F-stat)	0.21	0.26	0.57	0.36
Average post-LYOL	-0.001	-0.001	-0.000	0.000
Static post-LYOL	-0.001***	-0.001*	0.000	0.000*
d) Simple Counterfactual				
Pre-trends (F-stat)	0.20	0.51	0.90	0.08
Joint post-LYOL (F-stat)	0.31	0.23	1.21	0.15
Average post-LYOL	-0.000	-0.000	0.000	-0.000
Static post-LYOL	-0.000***	-0.000**	0.000	-0.000
e) Regression-Based Counterfactual				
Pre-trends (F-stat)	0.20	0.46	0.97	0.08
Joint post-LYOL (F-stat)	0.31	0.24	1.16	0.16
Average post-LYOL	-0.000	-0.000	0.000	-0.000
Static post-LYOL	-0.000***	-0.000**	0.000	-0.000

Notes: The table displays the estimated effects of end-of-life medical spending on surviving spouses' healthcare utilization. Estimates are reported for three measures of treatment intensity and two alternative constructions of the counterfactual, across panels a)–e). Each panel reports (i) a joint F-test for pre-trends ($k \leq -4$); (ii) a joint F-test for the post-LYOL event-study coefficients ($k > -4$) from Equation (5); (iii) the average post-LYOL effect from Equation (5); and (iv) the average static effect estimated by regressing outcomes on an indicator for the post-LYOL period ($k > -4$). Healthcare utilization is measured using indicator variables (0/1). Data on health outcomes are from the Upper Austrian Health Insurance Fund and cover the period 2006–2018. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE B.20 — Event study estimates on labor market outcomes, alternative identification strategy, coefficients are multiplied by 100 for presentational purposes

	Employment		Sick Leave		Unemployment		Retirement		Out of LF	
	No FE	FE	No FE	FE	No FE	FE	No FE	FE	No FE	FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
t=-16	0.0031	0.0031	0.0002	0.0002	-0.0010	-0.0010	-0.0011	-0.0010	-0.0000	-0.0000
t=-15	0.0034	0.0034	-0.0012	-0.0012*	-0.0005	-0.0005	-0.0010	-0.0009	-0.0000	-0.0000
t=-14	0.0038	0.0038*	0.0001	0.0001	-0.0007	-0.0007	-0.0015	-0.0014	-0.0000	-0.0000
t=-13	0.0033	0.0034	-0.0007	-0.0007	-0.0000	-0.0000	-0.0011	-0.0010	-0.0000	-0.0000
t=-12	0.0028	0.0028	-0.0003	-0.0003	-0.0000	-0.0000	-0.0006	-0.0005	-0.0000	-0.0000
t=-11	0.0004	0.0004	-0.0001	-0.0001	0.0004	0.0004	0.0008	0.0009	-0.0000	-0.0000
t=-10	-0.0001	-0.0001	0.0005	0.0005	0.0009	0.0009	0.0005	0.0006	-0.0000	-0.0000
t=-9	-0.0000	-0.0000	-0.0010	-0.0010	0.0005	0.0005	0.0005	0.0006	-0.0000	-0.0000
t=-8	0.0014	0.0014	-0.0001	-0.0001	-0.0004	-0.0003	0.0003	0.0004	-0.0000	-0.0000
t=-7	0.0017	0.0017	-0.0004	-0.0004	0.0005	0.0005	-0.0006	-0.0006	-0.0000	-0.0000
t=-6	-0.0003	-0.0003	0.0061***	0.0061	-0.0002	-0.0002	-0.0005	-0.0004	-0.0000	-0.0000
t=-5	-0.0006	-0.0006	0.0018	0.0018	-0.0002	-0.0002	-0.0004	-0.0004	0.0000	0.0000
t=-3	-0.0001	-0.0001	-0.0004	-0.0004	0.0007	0.0007*	0.0003	0.0003	-0.0000	-0.0000
t=-2	0.0001	0.0001	-0.0005	-0.0005	0.0005	0.0005	0.0006	0.0006	-0.0000	-0.0000*
t=-1	0.0000	0.0000	-0.0004	-0.0004	0.0007	0.0007	0.0002	0.0002	-0.0000	-0.0000
t=0	0.0003	0.0002	0.0001	0.0001	0.0015	0.0015**	-0.0003	-0.0003	-0.0000	-0.0000
t=1	-0.0010	-0.0010	0.0015	0.0015	0.0017*	0.0017**	-0.0007	-0.0007	-0.0000	-0.0000
t=2	-0.0004	-0.0004	0.0004	0.0004	0.0011	0.0011	-0.0009	-0.0009	-0.0000	-0.0000
t=3	0.0017	0.0016	-0.0003	-0.0003	0.0003	0.0003	-0.0017	-0.0018	-0.0000	-0.0000
t=4	0.0012	0.0012	-0.0002	-0.0002	0.0009	0.0009	-0.0018	-0.0018	-0.0000	-0.0000
t=5	0.0003	0.0003	0.0010	0.0010	0.0012	0.0012	-0.0018	-0.0019	-0.0000	-0.0000
t=6	0.0006	0.0006	0.0011	0.0011*	0.0016	0.0016*	-0.0019	-0.0019	-0.0000	-0.0000
t=7	0.0014	0.0013	0.0011	0.0011	0.0005	0.0005	-0.0012	-0.0012	-0.0000	-0.0000
t=8	0.0012	0.0012	0.0001	0.0001	0.0003	0.0003	-0.0012	-0.0012	-0.0000	-0.0000
t=9	0.0005	0.0005	-0.0009	-0.0009	0.0004	0.0004	-0.0012	-0.0012	-0.0000	-0.0000
t=10	0.0002	0.0002	-0.0009	-0.0009	0.0003	0.0004	-0.0013	-0.0013	-0.0000	-0.0000
t=11	-0.0000	0.0000	-0.0002	-0.0001	-0.0006	-0.0006	-0.0009	-0.0009	-0.0000	-0.0000
t=12	0.0002	0.0002	-0.0004	-0.0004	-0.0003	-0.0002	-0.0010	-0.0010	-0.0000	-0.0000
t=13	-0.0000	0.0000	-0.0004	-0.0004	0.0001	0.0002	-0.0007	-0.0007	-0.0000	-0.0000
t=14	0.0004	0.0004	-0.0000	0.0000	-0.0002	-0.0001	-0.0008	-0.0008	-0.0000	-0.0000
t=15	0.0008	0.0008	-0.0003	-0.0003	-0.0002	-0.0001	-0.0009	-0.0009	-0.0000	-0.0000
t=16	0.0004	0.0004	0.0000	0.0000	0.0002	0.0003	-0.0011	-0.0011	-0.0000	-0.0000
Observations	152,328	152,328	152,328	152,328	152,328	152,328	152,328	152,328	152,328	152,328
Mean outcome (t=-4)	3573.3118	3573.3118	165.8596	165.8596	234.0597	234.0597	3063.8956	3063.8956	20.9578	20.9578
Effect t=-2 (%)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Effect t=0 (%)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Effect t=8 (%)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Effect t=16 (%)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Disease FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spouse age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Notes: The table displays the estimated effects of end-of-life medical spending on surviving spouses' labor market outcomes from Equation (8), estimated both with and without individual fixed effects. All labor market outcomes are measured in days, with zero assigned when an individual is not in the respective labor market state. Coefficients are interpreted as effects per additional 1,000 € of excess end-of-life medical spending. Estimates are measured relative to the baseline of four quarters before death ($k = -4$). Data on labor market outcomes are from the Austrian Social Security Database and cover the period 2006–2018. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE B.21 — Event study estimates on healthcare utilization, alternative identification strategy, coefficients are multiplied by 100 for presentational purposes

	Physician Visit		Drug Use		Hospital Admission		Mental Health Care	
	No FE (1)	FE (2)	No FE (3)	FE (4)	No FE (5)	FE (6)	No FE (7)	FE (8)
t=-16	0.0000	0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000
t=-15	0.0000	-0.0000	0.0000	-0.0000	0.0000	0.0000	-0.0000	-0.0000
t=-14	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
t=-13	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	0.0000	0.0000
t=-12	0.0000	0.0000	0.0001	0.0001	0.0000	-0.0000	0.0000	0.0000
t=-11	0.0000	0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000
t=-10	-0.0000	-0.0001	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000
t=-9	0.0000	0.0000	0.0001	0.0001	-0.0000	-0.0000	0.0000	0.0000
t=-8	0.0000	0.0000	-0.0000	-0.0000	-0.0000	-0.0000	0.0000	0.0000
t=-7	0.0000	0.0000	0.0000	0.0000	-0.0000	-0.0000*	0.0000	0.0000
t=-6	0.0000	0.0000	0.0001	0.0001*	0.0000	0.0000	0.0000	0.0000
t=-5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-0.0000	-0.0000
t=-3	-0.0001	-0.0001	0.0000	0.0000	-0.0000	-0.0000	-0.0000	-0.0000
t=-2	0.0000	0.0000	0.0000	0.0000	-0.0000	-0.0000	0.0000	0.0000
t=-1	-0.0000	-0.0000	0.0000	0.0000	-0.0000	-0.0000	-0.0000	-0.0000
t=0	-0.0001	-0.0001	0.0000	0.0000	-0.0000	-0.0000	0.0000	0.0000
t=1	0.0000	0.0000	-0.0000	-0.0000	0.0000	0.0000	-0.0000	-0.0000
t=2	-0.0000	-0.0000	0.0001	0.0001	0.0000	0.0000	0.0000	-0.0000
t=3	0.0000	0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000
t=4	-0.0001	-0.0001	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000
t=5	-0.0001	-0.0001	-0.0001	-0.0001*	-0.0000	-0.0000**	0.0000	0.0000
t=6	0.0000	0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000
t=7	0.0000	0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000
t=8	-0.0001	-0.0001	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000
t=9	0.0000	0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000
t=10	-0.0001	-0.0001	-0.0000	-0.0000	0.0000	0.0000	-0.0000	-0.0000
t=11	0.0000	0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000
t=12	0.0000	0.0000	-0.0000	-0.0000	0.0000	0.0000	-0.0000	-0.0000
t=13	0.0000	0.0000	0.0001	0.0001	-0.0000	-0.0000	-0.0000	-0.0000
t=14	-0.0001	-0.0001	-0.0000	-0.0000	-0.0000	-0.0000	0.0000	0.0000
t=15	-0.0000	-0.0000	-0.0000	-0.0001	-0.0000	-0.0000	-0.0000	-0.0000
t=16	-0.0000	-0.0000	-0.0000	-0.0000	0.0000	0.0000	-0.0000	-0.0000
Observations	40,821	40,821	40,821	40,821	40,821	40,821	40,821	40,821
Mean outcome (t=-4)	40.9722	40.9722	29.8611	29.8611	2.7778	2.7778	5.9028	5.9028
Effect t=-2 (%)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Effect t=0 (%)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Effect t=8 (%)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Effect t=16 (%)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Disease FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spouse age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	No	Yes	No	Yes	No	Yes	No	Yes

Notes: The table displays the estimated effects of end-of-life medical spending on surviving spouses' healthcare utilization from Equation (8), estimated both with and without individual fixed effects. Healthcare utilization is measured using indicator variables (0/1). Coefficients are interpreted as effects per additional 1,000 € of excess end-of-life medical spending. Estimates are measured relative to the baseline of four quarters before death ($k = -4$). Data on health outcomes are from the Upper Austrian Health Insurance Fund and cover the period 2006–2018. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE B.22 — IV estimates on labor market outcomes

	Employment			Sick Leave			Unemployment			Retirement			Out of LF		
	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
LYOL spending	0.0639	-0.0763	0.0267	-0.0416	-0.0102	-0.0183	-0.0873	-0.1051	-0.1473	0.1731	0.3821	0.3701	-0.0058	-0.0068	-0.0081
	(0.4214)	(0.3821)	(0.5268)	(0.0686)	(0.0613)	(0.0927)	(0.1905)	(0.1814)	(0.2437)	(0.2742)	(0.2964)	(0.3948)	(0.0040)	(0.0043)	(0.0060)
Observations	2,396	2,393	2,392	2,396	2,393	2,392	2,396	2,393	2,392	2,396	2,393	2,392	2,396	2,393	2,392
Mean outcome (post-death)	24.7404	24.7404	24.7404	1.2142	1.2142	1.2142	1.7457	1.7457	1.7457	40.7881	40.7881	40.7881	0.2437	0.2437	0.2437
First-stage F-stat	38.82	61.88	21.68	38.82	61.88	21.68	38.82	61.88	21.68	38.82	61.88	21.68	38.82	61.88	21.68
Age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spouse age FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Disease FE	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes

Notes: The table reports two-stage least squares estimates of the effect of end-of-life medical spending on surviving spouses' labor market outcomes from Equation (9). Columns M1–M3 report specifications with progressively richer sets of controls. End-of-life medical spending is measured in the deceased spouse's last year of life and expressed in units of 1,000 €. Standard errors are clustered at the hospital level. Data on labor market outcomes are from the Austrian Social Security Database and cover the period 2006–2018. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.23 — IV estimates on healthcare utilization

	Physician Visit			Drug Use			Hospital Admission			Mental Health Care		
	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
LYOL spending	0.0040	0.0084	0.0044	0.0014	0.0046	0.0024	0.0003	0.0013	0.0034	-0.0077	-0.0063	-0.0104
	(0.0157)	(0.0120)	(0.0174)	(0.0173)	(0.0150)	(0.0254)	(0.0014)	(0.0010)	(0.0020)	(0.0093)	(0.0095)	(0.0182)
Observations	776	776	775	776	776	775	776	776	775	776	776	775
Mean outcome (post-death)	0.4936	0.4936	0.4936	0.3963	0.3963	0.3963	0.0391	0.0391	0.0391	0.0944	0.0944	0.0944
First-stage F-stat	15.42	12.21	4.19	15.42	12.21	4.19	15.42	12.21	4.19	15.42	12.21	4.19
Age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spouse age FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Disease FE	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes

Notes: The table reports two-stage least squares estimates of the effect of end-of-life medical spending on surviving spouses' healthcare utilization from Equation (9). Columns M1–M3 report specifications with progressively richer sets of controls. End-of-life medical spending is measured in the deceased spouse's last year of life and expressed in units of 1,000 €. Standard errors are clustered at the hospital level. Data on health outcomes are from the Upper Austrian Health Insurance Fund and cover the period 2006–2018. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C. Hoover adjustment

Because individuals who die are only observed for the portion of their final calendar quarter that they survive, spending recorded in the quarter of death mechanically understates true end-of-life healthcare use. To address this, we apply the adjustment proposed by Hoover et al. (2002), which estimates what spending would have been had each individual survived the full three-month period.

For each decedent, we first measure the fraction of the quarter they were alive:

$$m_i = (\text{month within quarter}_i - 1) + \frac{\text{day of death}_i}{\text{days in death month}_i}, \tag{C.1}$$

where m_i ranges from approximately 0 (death at the start of the quarter) to 3 (survival through the full quarter). We then estimate the empirical relationship between spending and exposure time using a flexible polynomial model:

$$\text{Expenditure}_i = \beta_0 + \beta_1\sqrt{m_i} + \beta_2 m_i + \beta_3 m_i^2 + \varepsilon_i. \tag{C.2}$$

This non-linear specification reflects the well-documented pattern that healthcare spending accelerates sharply near death, rather than accumulating proportionally over time. Using the estimated coefficients, we compute two predicted values:

$$\widehat{Y}_i(m_i) = \hat{\beta}_0 + \hat{\beta}_1\sqrt{m_i} + \hat{\beta}_2 m_i + \hat{\beta}_3 m_i^2, \tag{C.3}$$

which represents the model-predicted spending based on the fraction of the quarter an individual survived, and

$$\widehat{Y}_i^{(3)} = \hat{\beta}_0 + \hat{\beta}_1\sqrt{3} + 3\hat{\beta}_2 + 9\hat{\beta}_3, \tag{C.4}$$

which corresponds to predicted spending for a full quarter of observation. The adjustment factor is then defined as the ratio of these two predicted values:

$$\text{Adjustment factor}_i = \frac{\widehat{Y}_i^{(3)}}{\widehat{Y}_i(m_i)}. \tag{C.5}$$

Intuitively, this factor reflects how much observed spending must be scaled to represent full-quarter exposure. It is close to one for individuals who lived most of the quarter and larger for those who died shortly after the quarter began.

Observed spending in the death quarter is multiplied by this factor, while spending in all other quarters remains unchanged. Finally, adjusted totals are proportionally allocated across spending categories (inpatient care, physician services, and pharmaceuticals) based on each individual's observed spending composition, ensuring that component-level values sum exactly to the adjusted total.

D. Mortality prediction model

To characterize patients' ex-ante mortality risk, we estimate an individual-level prediction model using demographic characteristics, baseline healthcare utilization, and clinical information observed at the time of terminal disease diagnosis.

Specifically, we estimate a probit model for whether patient j dies during the observation window:

$$\Pr\left(\text{Death}_j = 1 \mid X_j\right) = \Phi\left(f\left(\text{age}_j\right) + g\left(S_j^{\text{pre}}\right) + \gamma' Z_j\right), \tag{D.1}$$

where Death_j indicates whether patient j dies during follow-up, $\Phi(\cdot)$ denotes the standard normal cumulative distribution function, and X_j contains all observable characteristics measured at or prior to the quarter of diagnosis.

The functions $f(\cdot)$ and $g(\cdot)$ are flexible cubic polynomials in age at diagnosis and total medical spending prior to diagnosis, respectively. Age captures systematic differences in baseline mortality risk over the life course, while pre-diagnosis spending serves as a proxy for underlying health status and healthcare needs before the onset of terminal illness.

The vector Z_j includes additional demographic and clinical controls. Demographic characteristics comprise indicators for sex, nationality, and educational attainment, measured using a binary indicator for university education. Clinical controls include diagnosis fixed effects based on the patient's first recorded terminal condition and diagnosis-year fixed effects. Diagnosis fixed effects capture differences in disease severity, progression, and expected survival across terminal illnesses, while diagnosis-year fixed effects account for secular changes in survival prospects, medical technologies, and treatment practices over time.

To capture baseline comorbidity burden, we also include the Charlson Comorbidity Index (CCI) in the mortality prediction model (Charlson et al., 1987). Comorbidities are aggregated to the patient level using standard Charlson weights, excluding conditions corresponding to the terminal diagnosis to avoid mechanically capturing severity related to the terminal illness itself. The index combines multiple comorbidities into a single weighted measure, where higher scores correspond to a heavier disease burden and a higher risk of death. The CCI enters the model as a continuous covariate, allowing baseline mortality risk to increase smoothly with overall disease burden.