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ABSTRACT

We estimate the causal impacts of GLP-1 treatment on labor market outcomes using linked Danish administrative data and a matched stacked difference-in-differences design. We compare patients who initiate GLP-1 treatment during the first two years of Semaglutide availability to observably similar patients who initiate four years later. We find that GLP-1 treatment reduces long-term sickness leave by 17.3%. We estimate total fiscal benefits of GLP-1 initiation of approximately 1.3–1.5% of annual labor income per employed individual. We do not detect statistically significant or economically meaningful impacts on income, labor force participation, or employment over four years.

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1 Introduction

Obesity and type 2 diabetes are two of the most prevalent chronic conditions in developed countries. Across OECD countries, almost one in four adults is obese, and diabetes affects 7% of adults (OECD, 2019, 2023). The economic burden of these conditions is substantial. Treating obesity-related diseases costs an estimated USD PPP 425 billion per year across OECD, G20, and EU28 countries (OECD, 2019). In the United States alone, the direct and indirect costs of diagnosed diabetes reached USD 413 billion in 2022 (Parker et al., 2024). A substantial share of these costs arises through the labor market, including through lower employment, reduced productivity, and increased absenteeism (OECD, 2019). GLP-1 receptor agonists have emerged as one of the most promising pharmaceutical innovations for the treatment of obesity and diabetes, with the potential to generate meaningful improvements in work capacity and labor market attachment.[1] In this paper, we study the causal effects of GLP-1 treatment on labor market outcomes.

Despite the rapid diffusion of GLP-1 drugs, rigorous causal evidence on their labor market impacts remains scarce for at least two reasons. The first is selection into treatment, as patients who initiate GLP-1 treatment differ from non-initiators in observed and potentially unobserved characteristics that may also relate to labor market outcomes. The second is lack of data. Addressing this question requires linked longitudinal records that follow the same individuals across prescription histories, health outcomes, and labor market trajectories over a sufficiently long horizon to detect downstream effects.

Our work overcomes these challenges using linked Danish administrative data and a matched stacked difference-in-differences design. We compare patients who initiate GLP-1 treatment during the first 17 months of availability (August 2018 to December 2019) to observably similar patients who initiate treatment 48 months later (August 2022 to December 2023).[2] To improve comparability, we first exact-match patients on key baseline characteristics, then implement nearest-neighbor propensity score matching within exact-match strata. This yields a matched sample of 7,011 early initiators and 7,011 later initiators. We then estimate a stacked difference-in-differences event study that traces outcomes over a four-year horizon.

We begin by documenting a strong and persistent first stage in GLP-1 use. Four years after initiation, 75% of treated patients remain on GLP-1 treatment. This level of persistence is substantially higher than in estimates from U.S. commercially insured populations, where 40 to 60% of patients adhere by the end of the first year (Wing et al., 2026). This difference suggests that prescription drug affordability may be an important determinant of long-run adherence. More broadly, it implies that expanded coverage and lower

[1] GLP-1 receptor agonists are a class of drugs that mimic endogenous glucagon-like peptide-1 to stimulate insulin secretion, suppress glucagon release, and at higher doses promote weight loss through appetite regulation.

[2] Within the GLP-1 class, Semaglutide represented a substantial advance over earlier agents in terms of glycemic control, weight loss, and cardiovascular risk reduction (Marso et al., 2016a). Semaglutide is marketed under two brand names targeting different indications: Ozempic for type 2 diabetes and Wegovy for obesity. We focus on Ozempic as it provides the longest available follow-up for Semaglutide treatment in Denmark. Ozempic became available in August 2018, while Wegovy was not introduced until December 2022. In Appendix C, we estimate qualitatively similar causal impacts of Wegovy initiation for weight management using a design adapted for that setting.

out-of-pocket costs—policies under consideration in many health systems—may not only affect treatment uptake, but also patients' ability to remain on therapy. Empirically, this persistent treatment exposure also increases the scope for detecting downstream effects over a four-year horizon.

We next examine the effects of GLP-1 treatment on long-term sickness leave, defined as spells exceeding 30 days. We find that treatment reduces long-term sickness leave by 0.95 percentage point (pp), corresponding to a 17.3% decline relative to the pre-initiation mean of 5.5%. The effect grows from roughly 0.8 pp in the first two post-initiation years to 1.1 pp in years three and four. Over the same period, we document reductions in emergency department visits and cardiovascular drug use, suggesting that gradual improvements in underlying cardiometabolic health may contribute to reduced sickness leave.[3] These estimated impacts on long-term sickness leave imply annual combined employer and public fiscal savings of about DKK 4,766 (approximately 1.5% of annual earned income or USD 866) per treated employed individual. This highlights reduced sickness leave as an economically meaningful channel through which these drugs generate value beyond their direct health effects.

Despite finding a meaningful decline in long-term sickness leave, we estimate statistically precise null effects on employment and total income over a four-year horizon. We can rule out increases in employment of more than 0.4 pp and increases in total income of more than 0.7%. These null results also extend across subsamples defined by sex, age, and education, with no statistically significant improvements in any group. The absence of an effect on total income reflects the Danish sickness benefit system, which provides near-full income replacement in the case of illness for much of our sample. As a result, reductions in sickness absence primarily generate employer and public savings rather than higher measured income for workers. In settings where work-limiting illness is less fully insured, similar health improvements could instead appear more directly in earnings, hours, or job retention.

Our paper contributes to the literature on the economic effects of medical treatments. Prior work has documented labor market benefits of treatments for chronic pain (Garthwaite, 2012; Bütikofer and Skira, 2018), mental health conditions (Shapiro, 2022; Biasi et al., 2025; Bhalotra et al., 2025), and cancer (Daysal et al., 2025).[4] We add to this literature by documenting the labor market effects of a class of drugs that targets obesity and diabetes, two conditions that affect more than 800 million adults worldwide. We also contribute to the emerging economics literature on GLP-1 drugs. Existing work has focused primarily on medical spending and clinical outcomes. Bock et al. (2026) and Wing et al. (2026) study the effects of GLP-1 treatment on healthcare spending and find no statistically significant reduction in spending over a four- to five-year horizon, although Bock et al. (2026) document a decline in major adverse cardiovascular events among patients with pre-existing cardiovascular disease. Recent work has begun to examine broader

[3] This is consistent with clinical trial evidence showing that GLP-1s lowers the incidence of major adverse cardiovascular events (Marso et al., 2016b), which are likely to result in prolonged work absences.

[4] A related literature studies how health and wellness interventions affect productivity and labor market outcomes more broadly (Stephens and Toohey, 2022; Jones et al., 2019).

non-health outcomes of GLP-1 treatment, with mixed findings across settings and outcomes. Kaestner and Schiman (2026) study adults with diabetes in the Medical Expenditures Panel Survey and find little evidence of changes in mental health, self-rated health, employment, or marriage over short horizons of one to two years. Diamond (2026) studies GLP-1 use for weight loss among women in the Understanding America Study and finds large increases in employment among women who were not employed at baseline, and in marriage or cohabitation among women who were single at baseline. We add to this emerging literature by studying GLP-1 treatment in population-wide Danish administrative data that link prescription histories to health care utilization, medically certified sickness leave, and labor market outcomes. We document high adherence to GLP-1 treatment over four years and show that sustained exposure reduces medically certified sickness leave and generates meaningful fiscal spillovers.

The remainder of this paper proceeds as follows. The next section provides a brief background on GLP-1s and long-term sickness leave in Denmark. Section 3 details our data, variables, and sample. Section 4 presents our matching strategy. Section 5 presents our key results and back-of-envelope fiscal benefit calculations. The last section concludes.

2 Institutional Setting

2.1 GLP-1 Receptor Agonists in Denmark

Denmark has a tax-financed universal health insurance system in which general practitioners (GPs) serve as the primary point of contact for chronic disease management, including type 2 diabetes. Most patients with type 2 diabetes receive pharmacotherapy in general practice, with referrals to endocrinologists or diabetologists reserved for complex or treatment-resistant cases (Mailhac et al., 2024). Treatment of type 2 diabetes ranges from lifestyle modification to pharmacotherapy, with common drug classes including biguanides (metformin), SGLT2 inhibitors, DPP-4 inhibitors, sulfonylureas, and insulin. Ozempic became available in Denmark in August 2018.[5] Throughout our study period, Ozempic was indicated for adults with type 2 diabetes whose condition was inadequately controlled through diet, exercise, and prior antidiabetic medication. It was prescribed either in place of a metformin prescription if deemed unsuitable, or as an add-on therapy to existing diabetes treatment (Medicin.dk, 2026a). Eligible prescriptions are subsidized: adult patients face a sliding copayment schedule with a maximum annual out-of-pocket amount of DKK 4,300 in 2019 (approximately USD 681), while a one-month supply of Ozempic in 2019 was DKK 1,117 (approximately USD 212). (Medicinpriser, 2026).[6]

[5] Figure B.1 shows the number of patients using any Semaglutide, Ozempic, Wegovy, or Rybelsus over time. Wegovy was introduced in Denmark in December 2022.

[6] This is for a four-week pack of 0.25 mg. Prices declined substantially over the study period: from DKK 1,339 in 2018 to DKK 1,117 in 2019 and DKK 213 by 2026.

2.2 Long-Term Sickness Leave in Denmark

In Denmark, long-term sickness leave is covered through the sickness benefit system. Eligibility generally requires that the individual be unable to work because of their illness and that they have sufficient labor market attachment. Employees, self-employed individuals, and unemployed individuals who would otherwise be entitled to unemployment insurance benefits may qualify under separate eligibility rules. Employers cover the first 30 calendar days of their employees' sickness absence, either through continued wage payments or sickness benefits. After this period covered by the employer, the municipality takes over the provision of sickness benefits if the individual remains certified as unable to work and satisfies statutory eligibility conditions. Benefits are based on prior earnings and hours, subject to a cap. In 2019, the maximum allowable sickness benefit was DKK 4,355 per week (approximately USD 2,831 per month). For workers with earnings below the cap, sickness benefits can therefore replace 100% of prior earnings, while benefits for higher earners are capped (Beskæftigelsesministeriet, 2026).

3 Data and Variables

We use several population-wide Danish administrative registers, linked at the individual level using unique personal identifiers. As detailed in Section 4, we compare early Ozempic initiators to matched later initiators in a stacked difference-in-differences design. This section describes measurement of treatment initiation, treatment persistence, outcomes, and baseline covariates. Further details are provided in Appendix A.

GLP-1 prescriptions. We obtain Semaglutide prescriptions from administrative records covering the universe of filled prescriptions in Denmark. We define treatment initiation as the date of an individual's first Ozempic prescription, requiring that this also be the individual's first Semaglutide prescription. We then construct an indicator for any Semaglutide prescription fill in each quarter. This measure serves as our first stage outcome and captures persistence in treatment after initiation.

Long-term sickness leave. Our main outcome variable captures long-term sickness leave, defined as a sickness spell lasting more than 30 days.[7] First, we measure the share of months in each quarter with any long-term sickness leave. We construct this measure from weekly administrative data on public transfer payments, from which we define monthly indicators for long-term sickness leave that we then average within each quarter. Second, we obtain municipality-paid sickness leave benefits from annual tax records, which capture payments made only after the first 30 days of a sickness spell, since employers are reimbursed by

[7] In a complementary data set, we observe all sickness absences, including those lasting fewer than 30 days, for employees in the public sector and in private firms with more than 250 employees. Since only 39% of our sample are employed in such firms at baseline, we use these data for robustness checks and supplementary fiscal benefit calculations rather than for the main analysis.

the municipality only beyond that threshold.[8]

Additional outcomes. Our secondary labor market outcomes capture employment, labor force attachment, and total income. We define employment and being out of the labor force from annual data on labor force status at the end of November. We obtain annual total income from tax records. Total income includes earned income, income from self-employment, sickness benefits, and other public transfers. All monetary values are expressed in 2025 DKK. Because these outcomes are measured annually, we assign labor force status indicators to each quarter in the corresponding calendar year and allocate annual income in equal fourths across the four quarters of that year. We show in the appendix that our results are robust to using a yearly specification.

To shed light on the pathways through which GLP-1 treatment may affect work capacity, we also construct three healthcare utilization outcomes in a given quarter. The first is an indicator for any emergency department encounter, drawn from hospital records. The second is an indicator for any cardiovascular drug prescription, extracted from prescription records using ATC code C. The third is the number of GP services received, obtained from national health insurance claims data.

Baseline Covariates. We define type 2 diabetes using hospital contacts with an International Classification of Diseases (ICD-10) diagnosis code of E11 or filled prescriptions for diabetes medication. We define obesity using hospital contacts with an ICD-10 diagnosis code of E66, excluding E66.3 (overweight). We obtain marital status and region of residence from population records, highest educational attainment from education records, and the number of GP services from national health insurance claims data. Diabetes and obesity status are measured in 2016–2017 while other baseline covariates are measured in December 2017.

4 Empirical Strategy

To estimate the causal effects of GLP-1 treatment on labor market outcomes, we implement a stacked difference-in-differences design on a matched sample of observably similar early and later initiators. We begin by constructing a treated group consisting of patients who first initiate Ozempic treatment during the first two calendar years of availability, from August 2018 through December 2019. The comparison group consists of patients who first initiate treatment four years later, from August 2022 through December 2023. This early-versus-later initiator design allows us to trace treatment effects over a four-year horizon. This comparison is similar in spirit to the designs used in Wing et al. (2026) and Diamond (2026) and is implemented using a stacked difference-in-differences estimator (Cengiz et al., 2019; Deshpande and Li, 2019; Conti et al., 2025).

[8] For individuals covered by unemployment insurance, eligibility begins after 14 days.

A central challenge with an early vs later treated comparison is that GLP-1 adoption expanded rapidly over a short period (as shown in Figure B.1), so early and later initiators differ systematically in observed characteristics. Prior studies show that early initiators in Denmark are older and more likely to have diabetes than later adopters (Mailhac et al., 2024).[9] These differences raise concerns about comparability between early and later initiators. For example, early initiators may disproportionately consist of patients starting GLP-1 therapy to manage treatment-resistant diabetes and related comorbidities, whereas later initiators may be younger and healthier patients seeking treatment primarily for weight loss. If these groups would have followed different health and labor market trajectories even in the absence of treatment, a simple comparison of early and later initiators would yield biased estimates of GLP-1's causal effects.[10]

To improve comparability, we match early initiators to later initiators (who initiate 4 years later) using nearest-neighbor matching within exact-match strata (Ho et al., 2017; Jäger et al., Forthcoming; Schmieder et al., 2023; Bertheau et al., 2023).[11] We first exact-match patients on four key variables at the start of 2018: sex, age (in five-year bins), diabetes, and obesity status—the latter two measured over 2016–2017. We match on fixed 2018 characteristics because they provide a common pre-treatment baseline, whereas pre-initiation characteristics may already reflect endogenous changes related to treatment timing. Within these strata, we then one-to-one match early and later initiators on the propensity score estimated from marital status, educational attainment, region of residence, income, and number of general practitioner services, all measured at the start of 2018. This hybrid procedure combines two advantages: exact-matching imposes common support on a parsimonious set of key baseline characteristics while preserving most early initiators in the analysis sample. Nearest-neighbor matching on the propensity score within exact-match strata then selects later initiators that are similar to early initiators along a richer set of observed baseline covariates. We only ever match on cross-sectional baseline patient characteristics, and never on trends.

Equipped with the matched sample of early and later initiators, we estimate a stacked difference-in-differences event study. Specifically, we stack outcomes for individual i in calendar quarter t across sub-experiments s, where each sub-experiment compares one early-initiation cohort to its matched cohort of initiators 16 quarters later:

$$Y_{ist} = \alpha_i + \lambda_{s\tau} + \sum_{k=-8, k\neq -1}^{15} \beta_k \left(\mathbf{1}\{\tau_{ist} = k\} \times EarlyInitiator_{is} \right) + \varepsilon_{ist}. \tag{1}$$

where $EarlyInitiator_{is}$ is an indicator equal to one if patient i belongs to the early-initiation cohort in

[9] Columns 1 and 2 of Table 1 show the same pattern in our data. Bock et al. (2026) document a similar pattern in the U.S. Veterans Health Administration.

[10] As previously mentioned, we focus on initiators of Ozempic (as opposed to *e.g.*, Wegovy) to improve comparability of early vs later treated. Wegovy became available in Denmark in December 2022 to primarily manage weight loss; early initiators used Ozempic for diabetes and weight management.

[11] Zeltzer et al. (2023) employ a similar method, using Euclidean distance to determine the nearest-neighbor within an exact-match strata of a telehealth device adopter (vs non-adopter); Altındağ et al. (2026) employ propensity score within exact-match strata, with replacement.

sub-experiment s, α_i are individual fixed effects, and $\lambda_{s\tau}$ are sub-experiment-by-event-time fixed effects. Event-time τ_{ist} is defined relative to the initiation quarter of the early-initiation cohort in sub-experiment s, so that the later-initiation cohort serves as the not-yet-treated control group throughout the estimation window. We follow outcomes from eight quarters before to fifteen quarters after initiation, omitting quarter -1 as the reference period. Heteroskedastic-robust standard errors are clustered at the individual level. We exclude patient-quarter observations after a patient dies.[12] Under the standard parallel trends assumption that later initiators would have evolved like early initiators in the time periods around the early initiators' initiation date, β_k estimate the causal impact of GLP-1 treatment on outcomes. Pre-initiation coefficients allow us to assess the plausibility of this assumption.

Analysis Sample. Our analysis sample consists of all individuals in Denmark who initiate Ozempic for the first time between August 2018 and December 2019 or between August 2022 and December 2023. We restrict the sample to adults between the ages of 30 and 59 in December 2017 to ensure that all individuals are under age 65 by the end of the post-period, and thus more likely to be attached to the labor market. Of the 9,794 patients aged 30 to 59 who initiate Ozempic between August 2018 and December 2019, and of the 23,480 who initiate between August 2022 and December 2023, our matching procedure successfully matches 7,011 early initiators with a 71.6% match rate, to 7,011 later initiators.

Summary Statistics and Covariate Balance. Table 1 reports summary statistics for early and later Ozempic initiators before and after matching. Columns (1) and (2) show that, prior to matching, early and later initiators differ substantially along several dimensions. Early initiators are older, more likely to be male, and much more likely to have diabetes, consistent with prior evidence on Semaglutide adoption in Denmark (Mailhac et al., 2024). They also have lower annual income, lower employment, and higher rates of being out of the labor force than later initiators.

Columns (3) and (4) show that matching substantially improves balance. By construction, matched early and later initiators are nearly identical in sex, age, diabetes status, and obesity status. The matched groups are also closely balanced on marital status, education, baseline annual income, labor force status, employment, and long-term sickness leave. In the matched sample, 55% are male, the average age is about 50, and 84% had either a hospital diabetes diagnosis or a diabetes medication fill in 2016–2017. Our sample is relatively socioeconomically disadvantaged; over 80% have less than a four-year college-equivalent degree and annual income is approximately DKK 213,000 to 218,000.

Identification in our stacked difference-in-differences design relies on the parallel trends assumption rather than on balance in baseline levels. Still, the improved covariate balance supports the use of later

[12] 98.0% of early initiators remain alive four years after Ozempic initiation, whereas, by construction, all later initiators survive for at least four years. For reference, the corresponding four-year mortality risk for the average 50 year old male Dane is 1.2% (Statistics Denmark, 2025).

initiators as a comparison group. Section 5.3 presents robustness checks that assess the sensitivity of the estimates to alternative matching specifications and comparison groups.

5 Results

5.1 First Stage: Semaglutide

Figure 1 shows the effects of Ozempic initiation on any Semaglutide use and Table B.1 presents the corresponding difference-in-differences estimates.[13] By construction, the coefficient in the quarter of initiation equals one, since treated patients begin treatment in that quarter while the comparison group consists of patients who first initiate 16 quarters later. As a result, the coefficients on the subsequent quarters can be interpreted directly as treatment persistence (adherence). The figure shows high persistence in GLP-1 use. Although discontinuation is meaningful during the first year, adherence stabilizes markedly thereafter. From roughly quarter 6 onward, the share of treated patients remaining on GLP-1 treatment is relatively flat, with 75% still on treatment four years after initiation. This adherence rate is substantially higher than those reported in U.S. studies, suggesting that affordability may be an important determinant of long-run adherence (e.g., Wing et al., 2026, find that in U.S. commercially insured patients, adherence drops to 40-60% by the end of the first year). While prior work often emphasizes discontinuation due to side effects, our results indicate that prescription drug costs—precisely the margin targeted by many recent and proposed policies around the world—may also play a central role. More broadly, this persistent and sustained treatment exposure implies that our design is well-powered to detect downstream effects on labor market outcomes.

5.2 Long-Term Sickness Leave

Figure 2 presents the effects of Ozempic initiation on long-term sickness leave. Panel (a) reports effects on share of months with any long-term sickness leave in the quarter. Panel (b) shows the effect on quarterly sickness leave benefits paid by the municipality, which apply only after the first 30 days of the spell.

In panel (a), a statistically significant reduction in long-term sickness leave emerges by the end of the first year after initiation and becomes more pronounced in the second year and beyond. The decline is about 0.8 percentage points (pp) in the first two post-initiation years and roughly 1.1 pp in years 3 and 4. Aggregating over the entire four-year post period, the difference-in-differences estimate implies a 0.95 pp reduction relative to a pre-period mean of 5.5%, corresponding to a 17.3% decline. Figure B.3 shows very similar estimates using an alternative measure based on whether the individual has any month in a quarter with long-term sickness leave, as well as in a specification restricted to individuals in formal wage

[13] Because Wegovy was not available until December 2022, the vast majority of Semaglutide prescriptions during our study period are for Ozempic. Figure B.2 shows the first stage using only Ozempic prescriptions.

employment.

Panel (b) shows a parallel decline in the amount of sickness leave benefits received. Ozempic initiation reduces quarterly sickness leave payments paid by the municipality (*i.e.*, after 30 days) by DKK 168 relative to a pre-period mean of DKK 865, or a 19.4% effect. The dynamic pattern closely mirrors that for the extensive margin outcome: the reduction is smaller and more gradual in the first two years after initiation, followed by a larger and persistent decline in years 3 and 4. Because our sickness benefit measure only captures payments made after the first 30 days of a sickness spell, it understates the full reduction in sickness benefits paid by the employer and municipality. In particular, any avoided spell also reduces payments during the initial month of absence, which is approximately equivalent to a full month of earnings for many workers in our sample. Indeed, in a complementary data set that captures all sickness absences for individuals employed in the public sector and in large firms, we estimate a similar relative reduction in sickness absences of all lengths (see Table B.1.)

The reduction in long-term sickness leave is consistent with improvements in underlying cardiometabolic health. Randomized trials show that Semaglutide lowers the incidence of major adverse cardiovascular events among high-risk patients (Marso et al., 2016c; Lincoff et al., 2023). Consistent with this mechanism, Figure C.1 shows declines in emergency department encounters, cardiovascular medication use after initiation, and GP services. Because acute cardiovascular and other emergency events are likely to generate prolonged medically certified absences, these patterns provide a plausible explanation for the decline in long-term sickness leave.

How large are these effects relative to the existing literature on pharmaceutical innovation and work capacity? The closest benchmark is Bütikofer and Skira (2018), who study the causal impacts of Vioxx cox-2 inhibitor pain medication on sickness absence days beyond the first 16 employer-paid days in Norway, rather than the probability of long-term sickness leave. While the outcomes are not directly comparable, our estimated 18% reduction is at least as large as their estimated effects of Vioxx, whose entry reduced sickness absence days among individuals with joint pain by 7 to 12% and whose withdrawal increased them by 12 to 16%.[14]

5.3 Robustness

We assess the robustness of our long-term sickness leave results using several alternative specifications and estimators, focusing throughout on our primary outcome: the share of months in the quarter with any long-term sickness leave. The result of these exercises can be found in Figure 3.

First, we vary the timing of covariate measurement in the matching procedure. Our baseline speci-

[14] Bütikofer and Skira (2018) report that, prior to Vioxx entry, 3.1% of male and 4.0% of female person-quarters among individuals with joint pain involved any sickness leave. In our data, 5.5% of person-months involve sickness leave lasting more than 30 days. Therefore, our estimated impacts of GLP-1 initiation are larger in both relative and absolute terms.

fication matches patients using fixed pre-period characteristics measured in 2016–2017. As an alternative, in panel (a), we match on characteristics measured in the year prior to each individual's own treatment initiation. For example, a 2018 initiator is matched on 2017 diabetes and obesity status, while a 2022 initiator is matched on the corresponding 2021 measures. All other features of the matching procedure are unchanged. This exercise assesses whether the results are sensitive to matching on patients' immediate pre-initiation clinical state, which aligns treatment need at the time of initiation, rather than on fixed baseline characteristics.

Second, we consider two alternative comparison group constructions motivated by the concern that patients initiating four years apart may not be the ideal counterfactual. We first implement the Callaway and Sant'Anna (2021) estimator using later-initiation patients as controls (panel b). Relative to our baseline stacked design, which fixes the comparison group to patients initiating 16 quarters later, this approach uses all later-treated cohorts for each cohort-time comparison, yielding a substantially larger estimation sample of 59,443 initiators. Consequently, the longest-horizon estimates are identified from a sample very similar to the baseline design, while the earlier post-treatment coefficients draw on a broader set of later initiators that initiate closer in time to the early initiators and may therefore provide a more credible counterfactual. In this sense, the estimator delivers the main advantage of shortening the treatment-control gap, while also providing a useful robustness check for the short- and medium-run dynamics and, as expected, increasing precision at shorter horizons.

Third, we restrict the sample to the first four initiation cohorts, from 2018Q3 through 2019Q2, excluding the final two early-treatment quarters whose matched controls initiate in late 2023 and may therefore lie on different underlying outcome trajectories (panel c). A further advantage of this restriction is that it increases the match rate to 87.0%. Across all three alternative specifications and estimators, our main findings are robust. Ozempic initiation reduces long-term sickness leave by about 1–1.5 pp, with effects peaking shortly after the second year.

Finally, we examine whether our findings for Ozempic initiation extend to Wegovy for weight management, the Semaglutide formulation used for weight management and a rapidly expanding treatment margin. In Appendix C, we follow the design of Diamond (2026) and show that our results for long-term sickness leave and broader labor market outcomes are qualitatively similar to our main findings.

5.4 Additional Labor Market Outcomes

Figure 4 turns to effects on our secondary labor market outcomes: labor force participation, employment status, and log total income. Across these outcomes, we find no statistically significant or economically meaningful effects. The two-period difference-in-differences estimate for being out of the labor force is 0.0019 (SE = 0.0042). Given a baseline mean of 32%, this allows us to rule out reductions of more than 0.6

pp at the 95% confidence level. Similarly, the estimate for employment is −0.0046 (SE = 0.0045) relative to a baseline mean of 65.3%, allowing us to rule out employment gains larger than 0.4 pp. For log total income, the estimate is −0.72 (SE = 0.74), implying that we can rule out income increases exceeding 0.7% relative to a baseline mean of DKK 291,758. All difference-in-differences estimates are reported in Table B.1. Figure B.5 shows that the results are unchanged when we estimate them at the yearly-level instead of quarterly.

5.5 Heterogeneity

We examine heterogeneity in treatment effects by estimating two-period difference-in-differences models separately by sex, age, and baseline educational attainment. Figure B.6 reports the results. The reduction in long-term sickness leave is evident across nearly all subsamples. The point estimates are negative in every group, although the estimates for men and individuals under age 50 are less precise. This pattern implies that the reduction in long-term sickness leave among early Ozempic initiators in Denmark is not concentrated in a particular subgroup.

By contrast, we detect no statistically significant improvements in labor force participation, employment, or total income in any subsample. Men and individuals with less than a college education are less likely to be employed. Women experience the largest reductions in long-term sickness leave, and while the corresponding point estimates also suggest modest employment gains, these are neither statistically significant nor economically large: the employment estimate is 0.8 pp, with a 95% confidence interval of −0.5 to 2.1 pp.[15]

5.6 Fiscal Spillovers of GLP-1s

Finally, we provide a back-of-the-envelope assessment of the combined employer and public fiscal savings associated with the decline in long-term sickness leave. The calculation proceeds in three steps, using the estimates for the share of months with long-term sickness leave and for municipality-paid sickness leave benefits after the first 30 days (Figure 2, panels a and b) as key inputs.

We first compute fiscal savings during the initial 30 days of long-term sickness absence, when employers bear the cost. Ozempic reduces long-term sickness leave by 0.114 ($= 0.0095 \times 12$ months) months per treated patient per year. At the average annual labor income of DKK 214,217 and assuming 100% wage replacement during the first 30 days, this implies DKK 2,035 less sickness compensation per year, per GLP-1 initiating patient.

We next add savings beyond the first 30 days, which accrue to the municipality. The estimated

[15] These confidence intervals lie well below the employment gains reported by Diamond (2026) for American women initiating GLP-1 treatment primarily for weight loss, a setting that differs from ours both institutionally and in sample composition. Her proposed mechanism operates in part through the obesity penalty, and the relevance of channels such as discrimination, productivity, and health may differ across the U.S. and Danish contexts and across the two study samples.

reduction in municipality-paid sickness benefits after 30 days is DKK 671 per year. Summing the two components and scaling by the share of employed individuals in our sample (0.65) yields total fiscal savings of DKK 4,163 per employed initiator per year, equivalent to 1.3% of annual labor income.

Finally, we extend the calculation to short-term sickness absences. Assuming the 17.3% reduction in long-term sickness leave also applies to sickness absences lasting fewer than 30 days,[16] the implied additional benefit is DKK 603 per employed worker per year.[17] Total annual benefits therefore rise from DKK 4,163, based only on long-term sickness leave, to DKK 4,766 (approximately USD 722) once shorter duration sickness absences are included, corresponding to 1.3 and 1.5% of annual labor income, respectively.[18] Applied to the average annual income of an American adult with diabetes, these percentages imply annual benefits of approximately USD 756 to 866.[19]

These estimates may not generalize directly to other institutional settings. In countries with less generous sickness leave systems, such as the United States, the direct fiscal savings we quantify will likely be smaller, since less of the cost of long-term absence is currently borne by employers or the public sector. The corresponding gains may instead show up as increased productivity, less presenteeism, and a lower risk that health shocks disrupt employment altogether. Even with this caveat, the estimated savings for Denmark are a real budgetary offset to the cost of GLP-1 treatment: they imply that the public cost of subsidizing these drugs is lower than the pharmacy cost alone would suggest.[20]

6 Conclusion

This paper provides new evidence on the economic consequences of GLP-1 treatment using linked Danish administrative data and a matched stacked difference-in-differences design. Comparing early Ozempic initiators to observably similar patients who initiate four years later, we find that GLP-1 treatment leads to a meaningful and persistent reduction in long-term sickness leave. This effect grows over time and is accompanied by declines in emergency department encounters and cardiovascular medication use, consistent with sustained treatment exposure and gradual improvements in underlying health. Even in the absence of detectable effects on employment or total income over four years, GLP-1 treatment generates meaningful fiscal

[16] In a separate data set covering all sickness absences for employees in the public sector and in private firms with more than 250 employees, we estimate a similar decline in all absences, which include short-term sickness absences lasting fewer than 30 days (column 7 of Table B.1). The relative effect size is approximately 8.7%, and the 95% confidence interval includes our baseline 17.3% estimate for long-term sickness leave.

[17] Among workers covered by the supplemental absence data, the average number of sickness-absence days in spells shorter than 30 days is 5.94 calendar days per year in 2017. Valued at calendar-day earnings, this corresponds to 1.63% of annual labor income, or DKK 3,486. Applying a 17.3% reduction yields an additional annual benefit of DKK 603.

[18] The savings from reduced short-term sickness absences and from the first 30 days of long-term sickness leave accrue to employers, whereas savings beyond day 30 accrue to the municipality. Therefore, the 55% of the combined savings accrue to employers.

[19] Authors' calculation using the 2023 Medical Expenditure Panel Survey for diabetic patients ages 30–59; average annual income is $56,720 in 2025 dollars.

[20] While negotiated net prices may differ from patient prices, these fiscal benefits remain substantially smaller than the current cost of GLP-1 treatments in 2026.

spillovers by reducing prolonged sickness absence, valued at 1.3–1.5% of annual labor income per employed individual.

These findings speak to ongoing policy debates over GLP-1 coverage, but several institutional features may shape how the magnitudes translate across settings. Early Danish Ozempic adopters are likely more clinically indicated than the marginal patients who would initiate under broader coverage expansions, so our estimates are best interpreted as bounding the gains among patients with clear medical need. Institutional context also matters: in the United States, for example, GLP-1 availability, sickness benefit systems, and public financing all differ from Denmark's, so the fiscal gains we identify through reduced long-term sickness leave need not map one-for-one into U.S. budget savings.

References

Altındağ, Onur, Jane Greve, and Yulya Truskinovsky, "Family Spillovers of Dementia," NBER Working Paper 34635, National Bureau of Economic Research 2026.

Bertheau, Antoine, Edoardo Maria Acabbi, Cristina Barceló, Andreas Gulyas, Stefano Lombardi, and Raffaele Saggio, "The Unequal Consequences of Job Loss across Countries," *AER: Insights*, 2023, *5* (3), 393–408.

Beskæftigelsesministeriet, "Sygedagpenge," https://bm.dk/satser/satser-for-2026/sygedagpenge 2026. Accessed 5 June 2026.

Bhalotra, Sonia, Meltem N. Daysal, and Mircea Trandafir, "Antidepressant Treatment in Childhood," CESifo Working Paper 12067, CESifo July 2025. Also circulated as IZA Discussion Paper No. 18069 and RFBerlin Working Paper No. 90/25.

Biasi, Barbara, Michael S. Dahl, and Petra Moser, "Career Effects of Mental Health: Evidence from an Innovation in Treating Bipolar Disorder," *Journal of Political Economy Microeconomics*, 2025.

Bock, Sam, Jasmin Moshfegh, and Jonathan Zhang, "Weighing the Impacts of GLP-1s: Quasi-Experimental Evidence From Provider Adoption," NBER Working Paper 34667, National Bureau of Economic Research January 2026.

Bütikofer, Aline and Meghan M. Skira, "Missing Work Is a Pain: The Effect of Cox-2 Inhibitors on Sickness Absence and Disability Pension Receipt," *Journal of Human Resources*, January 2018, *53* (1), 71–122.

Callaway, Brantly and Pedro H. C. Sant'Anna, "Difference-in-Differences with multiple time periods," *Journal of Econometrics*, December 2021, *225* (2), 200–230.

Cengiz, Doruk, Arindrajit Dube, Attila Lindner, and Ben Zipperer, "The Effect of Minimum Wages on Low-Wage Jobs," *The Quarterly Journal of Economics*, 2019, *134* (3), 1405–1454.

Conti, Gabriella, Rita Ginja, Petra Persson, and Barton Willage, "The Menopause "Penalty"," November 2025. Working paper, November 21, 2025.

Daysal, N. Meltem, William N. Evans, Mikkel Hasse Pedersen, and Mircea Trandafir, "Do Medical Treatments Work for Work? Evidence from Breast Cancer Patients," *American Economic Journal: Economic Policy*, nov 2025, *17* (4), 379–409.

Deshpande, Manasi and Yue Li, "Who Is Screened Out? Application Costs and the Targeting of Disability Programs," *American Economic Journal: Economic Policy*, 2019, *11* (4), 213–248.

Diamond, Rebecca, "GLP-1–Induced Weight Loss and the Female Obesity Penalty," Working Paper 35387, National Bureau of Economic Research June 2026.

Garthwaite, Craig L., "The Economic Benefits of Pharmaceutical Innovations: The Case of COX-2 In-

hibitors," *American Economic Journal: Applied Economics*, 2012, *4* (3), 116–137.

Ho, Daniel E., Kosuke Imai, Gary King, and Elizabeth A. Stuart, "Matching as Nonparametric Preprocessing for Reducing Model Dependence in Parametric Causal Inference," *Political Analysis*, 2017, *15* (3).

Jäger, Simon, Jörg Heining, and Nathan Lazarus, "How Substitutable Are Workers? Evidence from Worker Deaths," *American Economic Review*, Forthcoming.

Jones, Damon, David Molitor, and Julian Reif, "What Do Workplace Wellness Programs Do? Evidence from the Illinois Workplace Wellness Study," *The Quarterly Journal of Economics*, November 2019, *134* (4), 1747–1791.

Kaestner, Robert and Cuiping Schiman, "The Effects of GLP-1 Use on Mental Health, Self-rated Health, Employment and Marriage," NBER Working Paper 35198, National Bureau of Economic Research May 2026.

Lincoff, A. Michael, Kirstine Brown-Frandsen, Helen M. Colhoun, John Deanfield, Scott S. Emerson, Søren Esbjerg, Stina Hardt-Lindberg, G. Kees Hovingh, Steven E. Kahn, Robert F. Kushner et al., "Semaglutide and Cardiovascular Outcomes in Obesity without Diabetes," *New England Journal of Medicine*, 2023, *389* (24), 2221–2232.

Mailhac, Aurélie, Lars Pedersen, Anton Pottegård, Jens Søndergaard, Torben Mogensen, Henrik Toft Sørensen, and Reimar W Thomsen, "Semaglutide (Ozempic®) use in Denmark 2018 through 2023–user trends and off-label prescribing for weight loss," *Clinical epidemiology*, 2024, pp. 307–318.

Marso, Steven P., Stephen C. Bain, Agostino Consoli, Freddy G. Eliaschewitz, Esteban Jódar, Lawrence A. Leiter, Ildiko Lingvay, Julio Rosenstock, Jochen Seufert, Mark L. Warren et al., "Semaglutide and Cardiovascular Outcomes in Patients with Type 2 Diabetes," *New England Journal of Medicine*, 2016, *375* (19), 1834–1844.

Marso, Steven P, Stephen C Bain, Agostino Consoli, Freddy G Eliaschewitz, Esteban Jódar, Lawrence A Leiter, Ildiko Lingvay, Julio Rosenstock, Jochen Seufert, and Mark L Warren, "Semaglutide and cardiovascular outcomes in patients with type 2 diabetes," *New England Journal of Medicine*, 2016, *375* (19), 1834–1844.

Marso, Steven P., Stephen C. Bain, Agostino Consoli, Frederico Glass Eliaschewitz, Esteban Jódar, Lawrence A. Leiter, Ildiko Lingvay, Julio Rosenstock, Jürgen Seufert, Murray L. Warren et al., "Semaglutide and Cardiovascular Outcomes in Patients with Type 2 Diabetes," *New England Journal of Medicine*, 2016, *375* (19), 1834–1844.

Medicin.dk, "Ozempic," https://pro.medicin.dk/Medicin/Praeparater/8714 May 2026. Revised 20 May 2026.

_ , "Wegovy," https://pro.medicin.dk/Medicin/Praeparater/10247 May 2026. Revised 19 May 2026.

Medicinpriser, "Ozempic," https://medicinpriser.dk/Default.aspx?Navn=Ozempic 2026. Price period: 25.05.2026 - 07.06.2026. Last updated 04.06.2026.

OECD, *The Heavy Burden of Obesity: The Economics of Prevention* OECD Health Policy Studies, Paris: OECD Publishing, 2019.

_ , *Health at a Glance 2023: OECD Indicators*, Paris: OECD Publishing, 2023.

Parker, Emily D., Janice Lin, Troy Mahoney, Nwanneamaka Ume, Grace Yang, Robert A. Gabbay, Nuha A. ElSayed, and Raveendhara R. Bannuru, "Economic Costs of Diabetes in the U.S. in 2022," *Diabetes Care*, 2024, *47* (1).

Schmieder, Johannes F., Till von Wachter, and Jörg Heining, "The Costs of Job Displacement over the Business Cycle and Its Sources: Evidence from Germany," *American Economic Review*, 2023, *113* (5), 1208–1254.

Shapiro, Bradley T., "Promoting Wellness or Waste? Evidence from Antidepressant Advertising," *American Economic Journal: Microeconomics*, 2022, *14* (2), 439–477.

Statistics Denmark, "Life table (5 years tables) by time, age and sex: Denmark 2020–2024," https://www.lifetable.de/File/GetDocument/data/DNK/DNK000020202024CU1.pdf 2025. Statbank Denmark; accessed 16 June 2026.

Stephens, Melvin Jr. and Desmond Toohey, "The Impact of Health on Labor Market Outcomes: Evidence from a Large-Scale Health Experiment," *American Economic Journal: Applied Economics*, July 2022, *14* (3), 367–399.

Wing, Coady, Sih-Ting Cai, Daniel Sacks, and Kosali Simon, "Do GLP-1 Medications Pay for Themselves?," 2026. Working Paper.

Zeltzer, Dan, Liran Einav, Joseph Rashba, Yehezkel Waisman, Motti Haimi, and Ran D. Balicer, "Adoption and Utilization of Device-Assisted Telemedicine," *Journal of Health Economics*, July 2023, *90*, 102780.

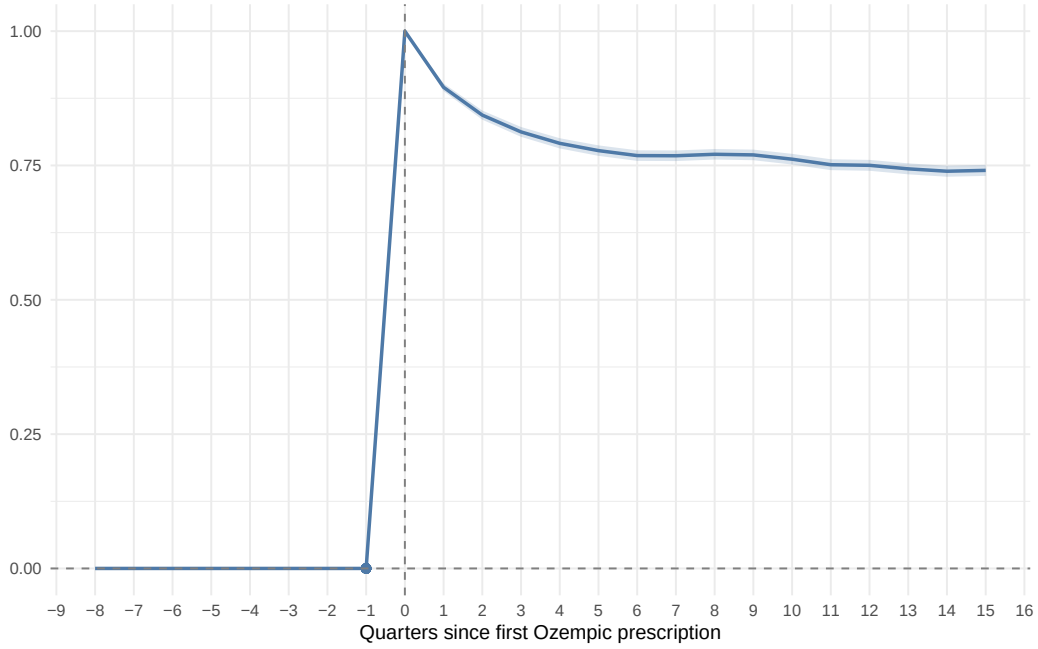
Tables and Figures

Table 1: Summary Statistics

	All Early Initiators (1)	All Late Initiators (2)	Matched Early Initiators (3)	Matched Late Initiators (4)	Absolute Standardized Difference (5)
Patient Characteristics					
Male	0.560	0.461	0.546	0.546	< 0.001
Diabetic	0.884	0.293	0.839	0.839	< 0.001
Obese	0.112	0.072	0.089	0.089	< 0.001
Age	50.20	47.69	49.93	49.92	0.001
	(6.87)	(7.68)	(6.98)	(6.99)	
Married	0.531	0.544	0.524	0.545	0.041
Unmarried	0.276	0.262	0.284	0.267	0.037
Divorced	0.177	0.182	0.174	0.172	0.004
Widowed	0.016	0.011	0.018	0.015	0.022
No Higher Education	0.366	0.302	0.385	0.365	0.041
Some Higher Education	0.451	0.457	0.445	0.453	0.016
More Higher Education	0.154	0.222	0.136	0.151	0.041
Outcomes					
Any Long-Term Sickness Leave	0.117	0.135	0.128	0.119	0.025
Sickness Leave Benefits	837.15	788.97	928.69	763.31	0.036
	(4,645.68)	(4,204.68)	(4,942.44)	(4,273.20)	
Out of Labor Force	0.305	0.223	0.325	0.302	0.050
Employed	0.667	0.747	0.648	0.667	0.040
Annual Total Income	224,167	267,008	213,761	217,776	0.019
	(214,995)	(219,257)	(212,649)	(206,081)	
Number of Observations	9,794	23,480	7,011	7,011	

Notes: This table presents summary statistics and covariate balance. Column (1) displays all early GLP-1 initiators (August 2018 – December 2019), column (2) displays all late GLP-1 initiators (August 2022 – December 2023). Columns (3) and (4) displays the subset of matched early and late initiators. Column (5) displays the absolute standardized differences (between columns 3 and 4). Diabetic status is defined as being on a diabetes medication or having a hospital diabetes diagnosis in 2016–2017 and obesity status is defined as having a hospital obesity diagnosis in 2016–2017. All other variables are measured in December 2017 and 2025 DKK. No, some, and more higher education are defined as anything equal to or less than upper secondary education; vocational training, short-cycle higher education; and vocational bachelors, bachelors, masters, PhD, respectively. Standard deviations are reported in parentheses below the means for non-indicator variables.

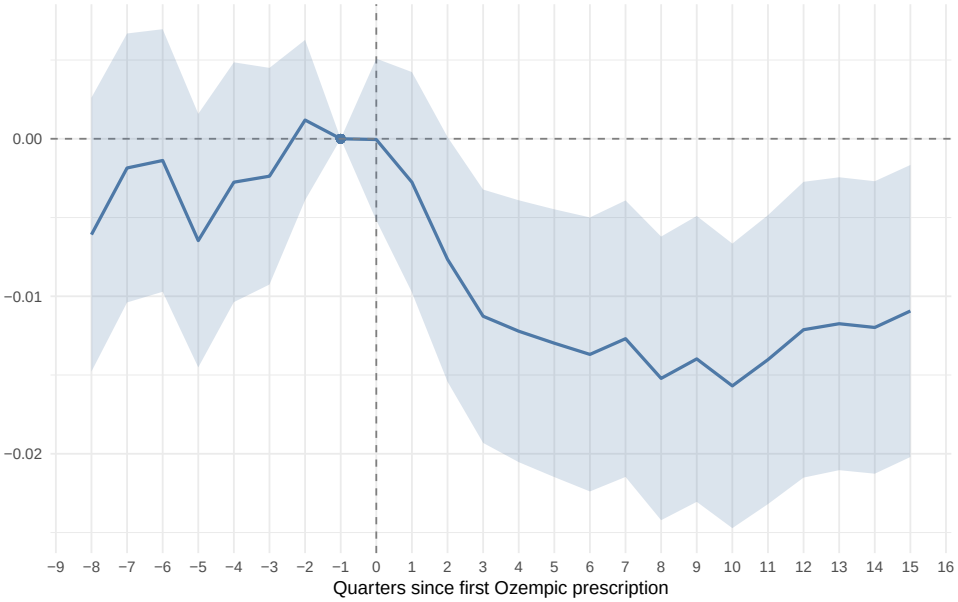
Figure 1: Any Semaglutide Prescription



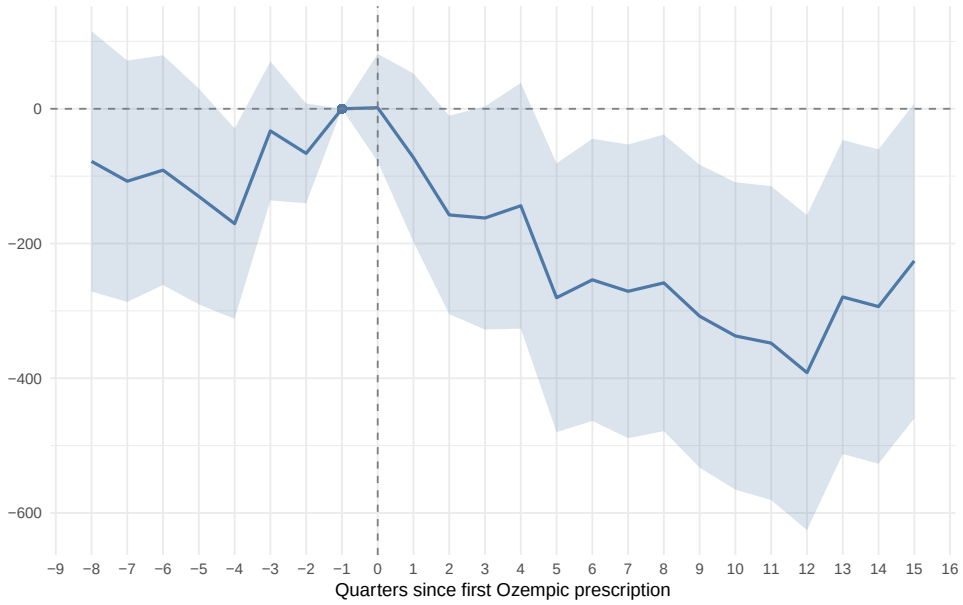
Notes: This figure plots the estimated event study coefficients from Equation 1 for any Semaglutide prescription in a given quarter. The sample consists of early Ozempic initiators (August 2018 to December 2019) matched to later initiators (August 2022 to December 2023). Patients are one-to-one exact-matched on sex, five year age bins, diabetes, and obesity status in 2016–2017 and propensity score matched within strata. The sample size consists of 14,022 patients, of which exactly half are early initiators. The outcome is any Semaglutide prescription in a given quarter, which includes Ozempic, Wegovy, and Rybelsus; however, the vast majority are Ozempic prescriptions. Figure B.2 shows the outcome for only Ozempic prescriptions. Patient-quarter observations that are dead are dropped. 95% confidence intervals constructed from heteroskedastic standard errors clustered at the individual-level are displayed.

Figure 2: Long-Term Sickness Leave

(a) Share of Months in the Quarter with Sick Leave



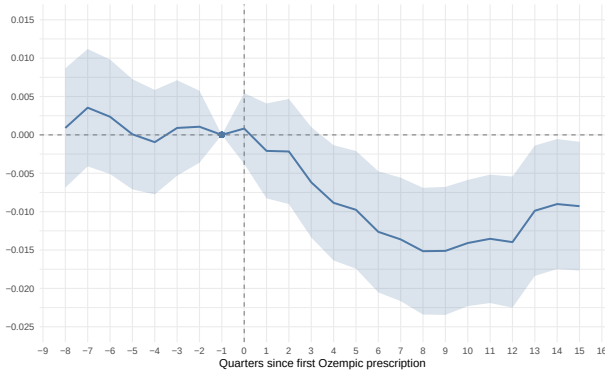
(b) Sick Leave Benefits Paid, after the first 30 days



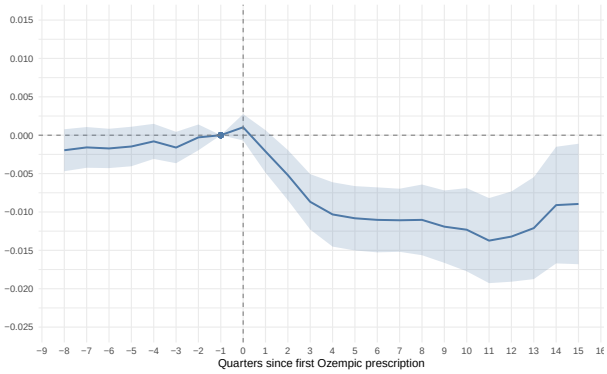
Notes: This figure plots the estimated event study coefficients from Equation 1 for our main long-term sickness leave outcomes. Panel (a) shows the extensive margin measure: the share of months in the quarter with any long-term sickness leave, constructed as the average of monthly indicators within the quarter. Since we observe the start date of each spell, the quarterly coefficients reflect the timing of sickness leave onset. Shorter sickness leave spells are not observed for all individuals. Panel (b) shows the intensive margin measure: the amount of municipality-paid sickness leave benefits (in 2025 Danish krone), on sick leave days after the first 30 days. Long-term sickness leave is defined as a spell lasting more than 30 days (14 days for self-employed individuals). The sample consists of early Ozempic initiators (August 2018 to December 2019) matched to later initiators (August 2022 to December 2023). Patients are one-to-one exact-matched on sex, five year age bins, diabetes, and obesity status in 2016–2017 and propensity score matched within strata. The sample size consists of 14,022 patients, of which exactly half are early initiators. Patient-quarter observations that are dead are dropped. 95% confidence intervals constructed from heteroskedastic standard errors clustered at the individual-level are displayed. Baseline means over the pre-period are 0.055 and DKK 865.

Figure 3: Robustness of Sickness Leave

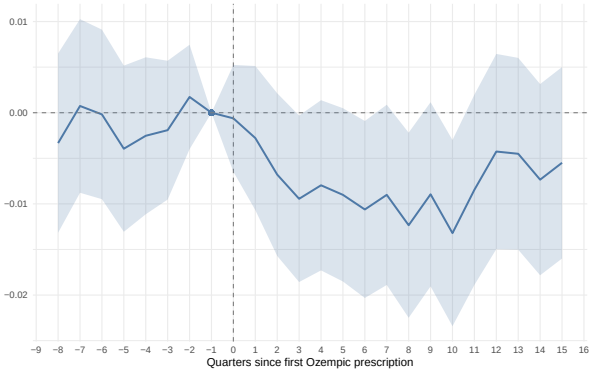
(a) Matching Based on Characteristics in Year Prior to Initiation



(b) Callaway and Sant'Anna



(c) First Four Initiation Cohorts (2018Q3 to 2019Q2)



Notes: This figure plots the estimated event study coefficients from Equation 1 for our main extensive margin long-term sickness leave (Figure 2 panel a) outcome using alternative specifications and estimators. Panel (a) uses the same propensity score within exact-match procedure but uses characteristics measured in the year prior to initiation instead of 2016–17 outcomes in the match (N=16,940, of which exactly half are early initiators).Panel (b) utilizes the Callaway and Sant'Anna (2021) estimator and later-treated as comparison group (N=59,443). Panel (c) matches only the first four initiation cohorts (2018Q3 to 2019Q2), which have a higher match rate of 87.0% (N=10,804, of which exactly half are early initiators). Individuals are restricted to ages 30-59 across all robustness exercises. Patient-quarter observations that are dead are dropped. 95% confidence intervals constructed from heteroskedastic standard errors clustered at the individual-level are displayed. Baseline means over the pre-period are 0.054, 0.070, and 0.054 for panels (a) to (c), respectively.

Figure 4: Labor Market Outcomes

Notes: This figure plots the estimated event study coefficients from Equation 1 for an indicator for being out of the labor force (panel a), indicator for being employed (panel b), log total income conditional on positive income (panel c; 99.6% of our patient-quarter observations have positive income). The sample consists of early Ozempic initiators (August 2018 to December 2019) matched to later initiators (August 2022 to December 2023). Patients are one-to-one exact-matched on sex, five year age bins, diabetes, and obesity status in 2016–2017 and propensity score matched within strata. The sample size consists of 14,022 patients, of which exactly half are early initiators. Patient-quarter observations that are dead are dropped. 95% confidence intervals constructed from heteroskedastic standard errors clustered at the individual-level are displayed. Baseline means over the pre-period are 0.32, 0.65, and 11.02 in log (mean total income is DKK 291,758), for panels (a) to (c), respectively.

Online Appendix for "The Labor Market Impacts of GLP-1s"

Table of Contents

A Data Sources **A.2**

B Appendix Tables and Figures **A.4**

C Wegovy Initiation for Weight Management **A.11**

A Data Sources

This appendix describes in more detail the Danish administrative registers used in this paper. All registers cover the entire population, can be linked at the individual level using unique personal identifiers, and span the period 2016–2024. Table A.1 details the construction of the variables used in the analysis.

GLP-1 prescriptions. We identify the date of treatment initiation and construct the indicator for any Semaglutide prescription fill from the *National Prescription Register* (*LMDB*). This register includes the universe of filled prescriptions in Denmark, regardless of payer, recording each drug's ATC code, the exact date when the prescription was filled, and the quantity dispensed. The ATC code classifies drugs by active chemical substance and therapeutic use, allowing us to distinguish products such as Ozempic and Wegovy.

Long-term sickness leave. We construct the share of months in each quarter with any long-term sickness leave based on the information in the *Danish Register for Evaluation of Marginalization* (*DREAM*), a weekly database of public transfer payments at the individual level. We obtain annual municipality-paid sickness leave benefits from the *Income Register* (*IND*), which provides annual information extracted from the tax records of every Danish resident.

Labor market outcomes. We construct the indicators for employment and for being out of the labor force based on the information in the *Register-Based Labor Force Statistics* (*RAS*). This register provides an annual snapshot of each Danish resident's labor market status at the end of November and is used by the Danish government to produce official labor market statistics. We obtain annual total income from the Income Register defined above.

Healthcare utilization. We construct the indicator for any emergency department encounter based on the information in the *National Patient Register* (*LPR*), which records all inpatient, outpatient, and emergency hospital contacts in public hospitals together with their diagnosis codes and the exact date of the contact. We use the National Prescription Register defined above to create the indicator for any cardiovascular drug prescription. Finally, we obtain the number of primary care services received from the *Health Insurance Register* (*SSSY*). This register consists of reimbursement claims submitted by general practitioners (GPs) and other specialists who contract with the national health insurance and operate outside of hospitals. Each claim includes the date of the contact, for both in-person and electronic contacts, and the services delivered during consultations. The *SSSY* unfortunately do not include diagnosis codes and none of our health data sets include biomarkers such as weight or blood glucose levels.

Baseline covariates. We construct the indicators for type 2 diabetes and obesity based on the diagnoses from the National Patient Register; for type 2 diabetes, we additionally use information on prescription fills for diabetes medication from the National Prescription Register. We obtain marital status and region of residence from the *Population Register* (*BEF*), which records demographic and household characteristics for every Danish resident on December 31 of each year. We obtain the highest educational attainment from the *Education Register* (*UDDA*), which details the highest completed qualification for every Danish resident as of September 30 of each year. Finally, we obtain the number of GP services from the Health Insurance Register.

Short-term sickness leave. We construct the number of days of absence from the *Absence from Work* data set (*FRPE*). This data set records the start and end dates of absence spells by cause, including own illness, child illness, and maternity or adoption leave. We restrict our attention to spells due to own illness. The data set covers the entire public sector, all private firms with at least 250 full-time employees, and a size- and industry-stratified sample of smaller private firms with at least 10 full-time employees that changes from year to year. For this reason, we restrict our attention to employees in the firms that are always included in the data set in every year (i.e., publicly-owned firms and privately-owned firms with at least 250 employees).

Table A.1: Data Sources

Variable	Definition	Years available	Registry name
Prescriptions and Diagnoses			
GLP-1 (Semaglutide)	Indicator for filled prescriptions of Semaglutide (ATC: A10BJ06); we also create a separate indicator for Ozempic from the brand name	2016–2023	National Prescription Register
Diabetes drugs	Indicator for filled prescriptions of diabetes drugs (ATC: beginning with 'A10')	2016–2023	National Prescription Register
Cardiovascular drugs	Indicator for any cardiovascular drug prescription in a given quarter (ATC: beginning with 'C')	2016–2023	National Prescription Register
Type 2 diabetes	Indicator based on hospital diagnosis codes (ICD-10: E11) or filled prescriptions for diabetes medication (ATC: beginning with 'A10')	2016–2024	National Patient Register; National Prescription Register
Obesity	Indicator based on hospital diagnosis codes (ICD-10: E66, excluding E66.3 overweight)	2016–2024	National Patient Register
Healthcare Utilization			
General Practitioner Services	Number of services received from the patient's general practitioner in a given quarter	2016–2024	Health Insurance Register
Emergency department encounter	Indicator for an emergency department hospital encounter in a given quarter	2016–2024	National Patient Register
Labor Market Variables			
Employment status	Indicators for being out of the labor force or employed, assigned from the November snapshot to all quarters of that year	2016–2024	Register-Based Labor Force Statistics
Long-term sickness leave (share)	Share of months in a quarter with sickness leave lasting more than 30 days	2016–2024	DREAM
Sickness leave benefits	Annual municipality-paid sickness leave benefits, allocated in equal fourths across quarters	2016–2024	Income Register
Total income	Annual sum of wage earnings, self-employment income, sickness benefits, and other public transfers, expressed in 2025 DKK and allocated in equal fourths across quarters	2016–2024	Income Register
Demographics and Covariates			
Age	Constructed from date of birth	2016–2024	Population Register
Marital/partnership status	Civil status, used to construct marital and partnership status	2016–2024	Population Register
Region of residence	From municipality of residence	2016–2024	Population Register
Educational attainment	Highest educational attainment, grouped into "no higher education" (equal to or less than upper secondary), "some higher education" (vocational training, short-cycle higher education), and "more higher education" (vocational bachelors, bachelors, masters, PhD)	2016–2024	Education Register

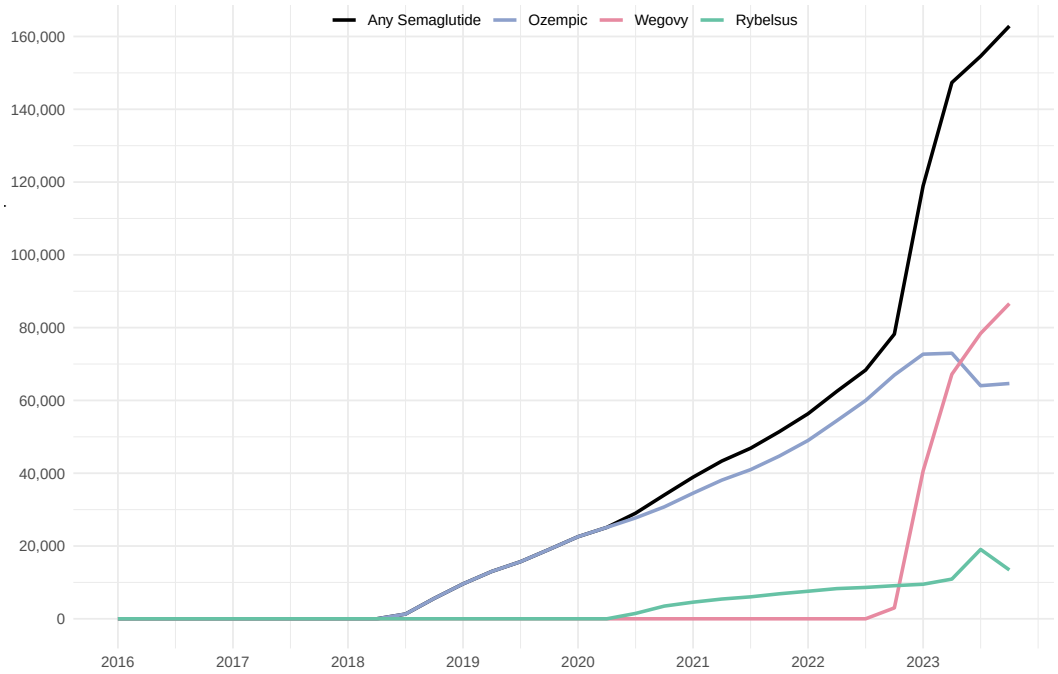
B Appendix Tables and Figures

Table B.1: Difference-in-Differences Estimates

	Dependent Variable:						
	Semaglutide Prescription	Long-Term Sick Leave	Sickness Benefits Paid, After 30 Days	OOLF	Employed	Log Total Income	Absent Days
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Aggregate Over Four Years:							
EarlyInitiator	0.779^{***}	-0.010^{***}	-167.70^{**}	0.0019	−0.0046	−0.0072	-0.248^{*}
	(0.004)	(0.003)	(81.17)	(0.0042)	(0.0045)	(0.0074)	(0.150)
Years 1–2:							
EarlyInitiator	0.808^{***}	-0.008^{***}	−107.1	0.0019	−0.0041	−0.0031	−0.230
	(0.004)	(0.003)	(83.57)	(0.0039)	(0.0043)	(0.0070)	(0.172)
Years 3–4:							
EarlyInitiator	0.753^{***}	-0.011^{***}	-220.70^{**}	0.0018	−0.0049	−0.0107	−0.298
	(0.004)	(0.003)	(96.60)	(0.0051)	(0.0054)	(0.0087)	(0.182)
Mean Dep. Var	0	0.055	865.30	0.3190	0.6530	11.02	2.875
Observations	322,506	322,506	322,491	322,313	322,313	321,334	120,360

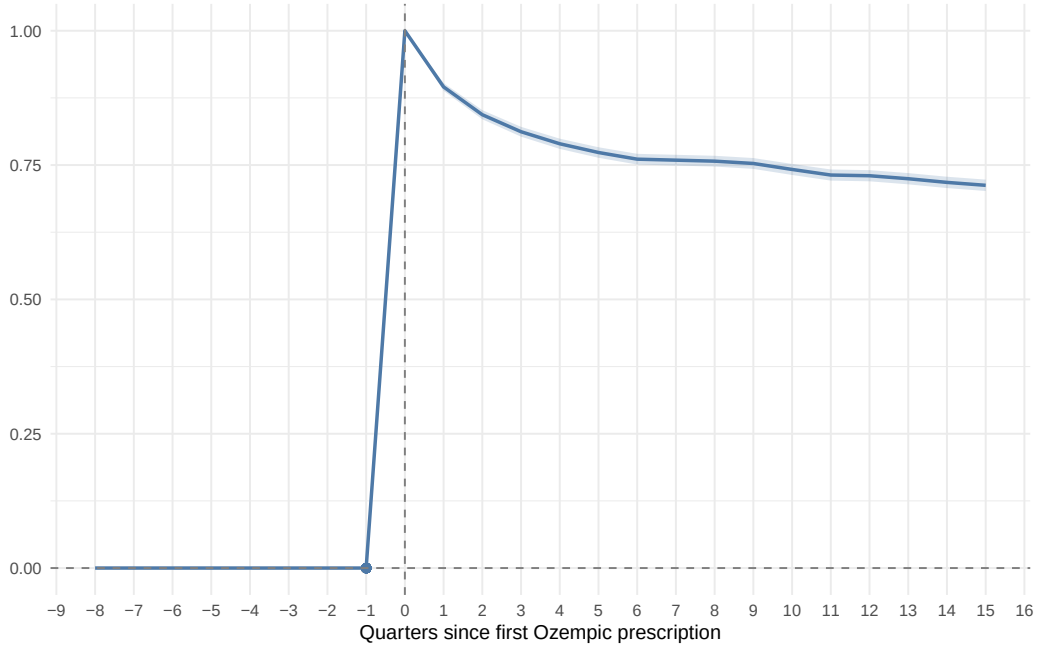
Notes: This table presents the aggregate difference-in-differences estimates that correspond to the event study specification in Equation 1. The top row displays the aggregate over the four-year post-period vs two-year pre-period. The middle row displays the aggregate over the first two-year post-period vs two-year pre-period. The bottom row displays the aggregate over the second two-year period (years 3–4) vs two-year pre-period. Means for the dependent variable correspond to the average over the pre-period. Log total income is conditional on positive total income (99.6% of our patient-quarter observations have positive income). Absent days (column 7) are defined as the number of calendar days an individual is absent due to sickness in a calendar quarter, and is only available for individuals employed in the public sector and firms with at least 250 employees and include all sickness absence lengths. Heteroskedastic standard errors clustered at the individual-level are displayed in parentheses. $p<0.1$; $p<0.05$; $p<0.01$.

Figure B.1: Time Series of Counts of Semaglutide Users, 2016–2023



Notes: This figure presents the number of all unique individuals filling Semaglutide prescription per quarter in Denmark, by type of Semaglutide. Our baseline analysis sample focuses on ages 30–59 in 2018, and initiators in August 2018 – December 2019 and August 2022 – December 2023.

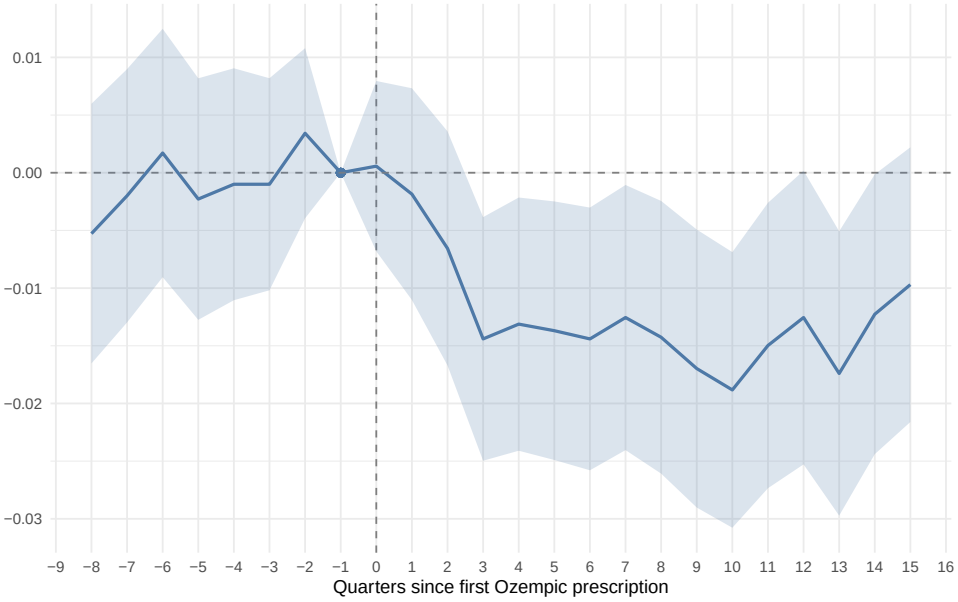
Figure B.2: Any Ozempic Prescription



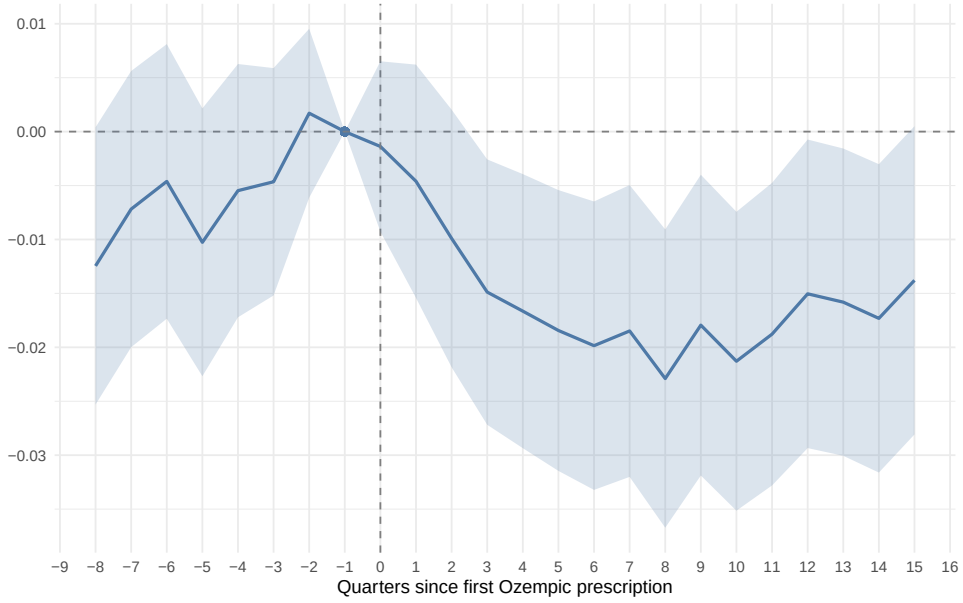
Notes: This figure plots the estimated event study coefficients from Equation 1 for any Ozempic prescription in a given quarter. The sample consists of early Ozempic initiators (August 2018 to December 2019) matched to later initiators (August 2022 to December 2023). Patients are one-to-one exact-matched on sex, five year age bins, diabetes, and obesity status in 2016–2017 and propensity score matched within strata. The sample size consists of 14,022 patients, of which exactly half are early initiators. The outcome is a subset of Figure 1 which includes both Ozempic and Wegovy prescriptions. Patient-quarter observations that are dead are dropped. 95% confidence intervals constructed from heteroskedastic standard errors clustered at the individual-level are displayed.

Figure B.3: Alternative Long-Term Sickness Leave

(a) Any Month in Quarter with Sickness Leave



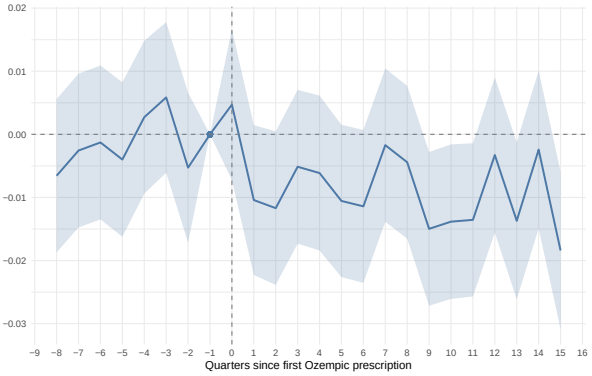
(b) Sickness Leave Conditional on Being in Labor Force



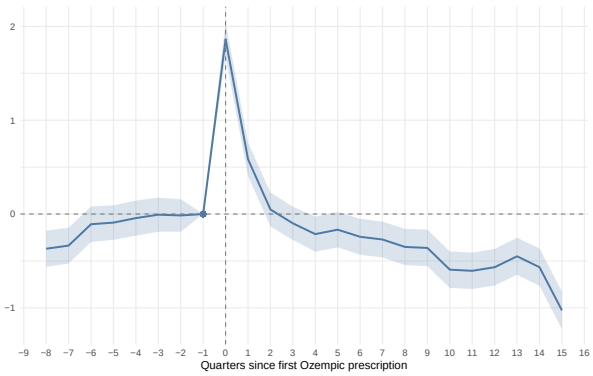
Notes: This figure plots the estimated event study coefficients from Equation 1 for alternate measures of long-term sickness leave. Panel (a) shows indicator for any month in a given quarter with long-term sickness leave (i.e., max instead of mean as in Figure 2 panel a) and panel (b) shows sickness leave conditional on being in the labor force for at least three months in 2017. Long-term sickness leave is defined as a spell lasting more than 30 days (14 days for self-employed or unemployed individuals). Since we observe the start date of each spell, the quarterly coefficients reflect the timing of sickness leave onset. Shorter sickness leave spells are not observed in the data. The sample consists of early Ozempic initiators (August 2018 to December 2019) matched to later initiators (August 2022 to December 2023). Patients are one-to-one exact-matched on sex, five year age bins, diabetes, and obesity status in 2016–2017 and propensity score matched within strata. The sample size consists of 14,022 patients, of which exactly half are early initiators. Patient-quarter observations that are dead are dropped. 95% confidence intervals constructed from heteroskedastic standard errors clustered at the individual-level are displayed. Baseline means over the pre-period are 0.08 and 0.08.

Figure B.4: Health-Related Outcomes and Utilization

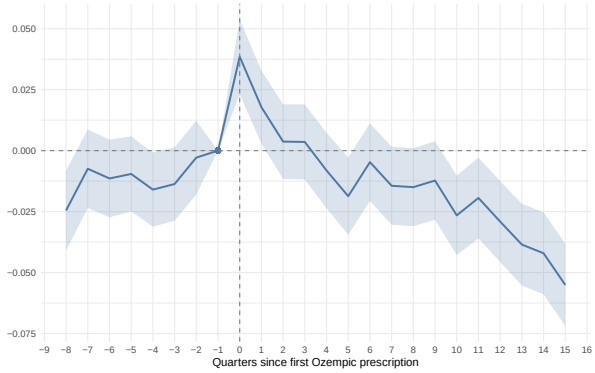
(a) Any Emergency Department Encounter



(b) Number of General Practitioner Services



(c) Any Cardiovascular Drug

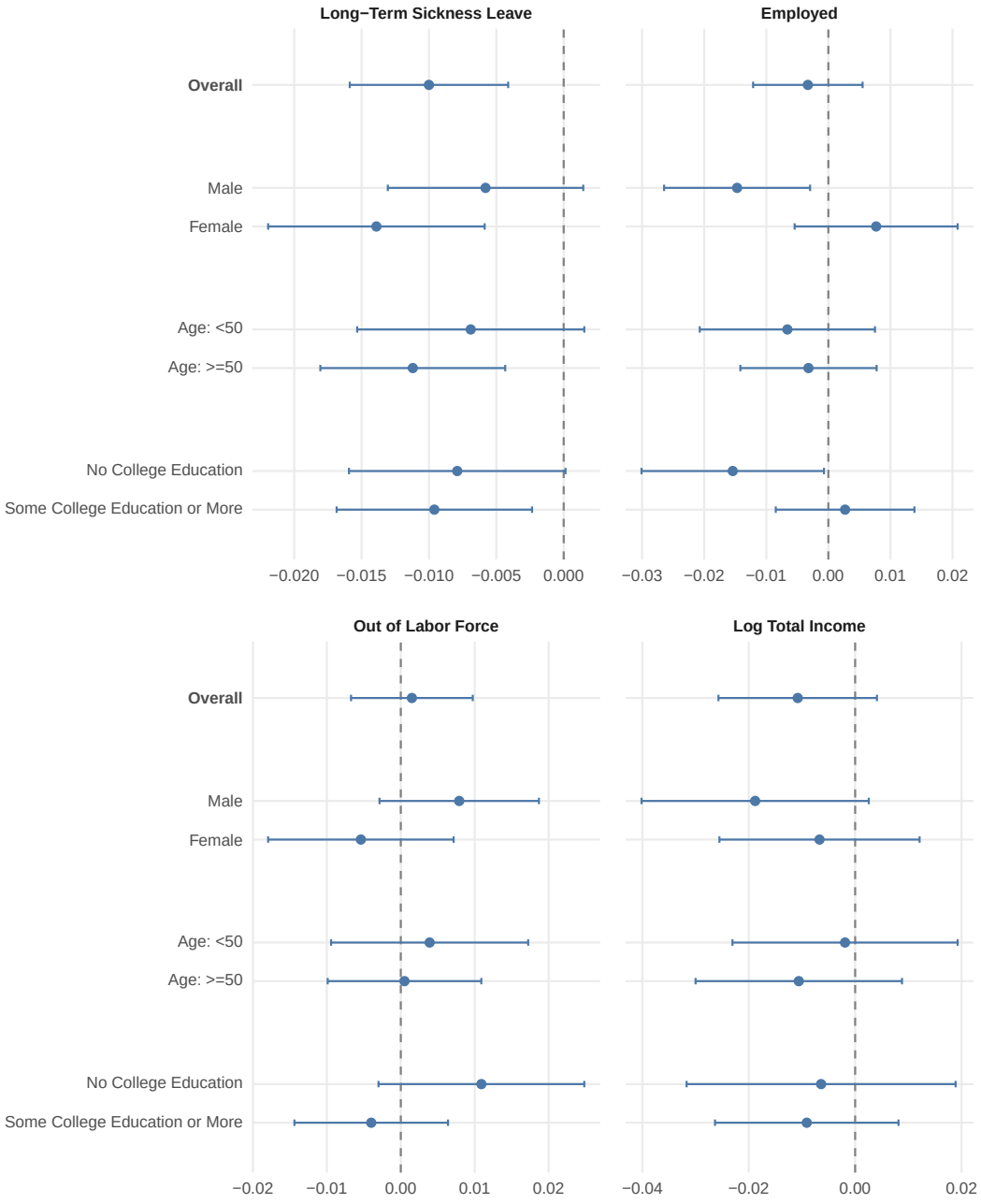


Notes: This figure plots the estimated event study coefficients from Equation 1 for health-related outcomes: any emergency department encounter, number of general practitioner services, and any cardiovascular drug prescription in a given quarter. Cardiovascular drugs are identified via ATC code 'C' which includes all drugs that target the cardiovascular system including antihypertensives, diuretics, beta blockers, calcium channel blockers, renin-angiotensin system agents, and lipid-lowering drugs. The sample consists of early Ozempic initiators (August 2018 to December 2019) matched to later initiators (August 2022 to December 2023). Patients are one-to-one exact-matched on sex, five year age bins, diabetes, and obesity status in 2016–2017 and propensity score matched within strata. The sample size consists of 14,022 patients, of which exactly half are early initiators. Patient-quarter observations that are dead are dropped. 95% confidence intervals constructed from heteroskedastic standard errors clustered at the individual-level are displayed. Baseline means over the pre-period are 0.08, 5.32, and 0.64.

Figure B.5: Labor Market Outcomes at the Yearly-Level

Notes: This figure plots the estimated event study coefficients from Equation 1 for an indicator for being out of the labor force (panel a), indicator for being employed (panel b), log total income conditional on positive income (panel c) using yearly labor market data. 99.6% of our patient-quarter observations have positive income. The sample consists of early Ozempic initiators (August 2018 to December 2019) matched to later initiators (August 2022 to December 2023). Patients are one-to-one exact-matched on sex, five year age bins, diabetes, and obesity status in 2016–2017 and propensity score matched within strata. The sample size consists of 14,022 patients, of which exactly half are early initiators. Patient-quarter observations that are dead are dropped. 95% confidence intervals constructed from heteroskedastic standard errors clustered at the individual-level are displayed. Baseline means over the pre-period are 0.32, 0.65, and 11.02 in log (mean total income is DKK 291,758), for panels (a) to (c), respectively.

Figure B.6: Heterogeneity Analysis – Difference-in-Differences Estimates



Notes: This figure plots difference-in-differences estimates over four-years for long-term sickness leave, indicator for out of labor force, indicator for being employed, and log total income conditional on positive total income (99.6% of our patient-quarter observations have positive income) for three subsamples corresponding to three margins of heterogeneity: sex, age, and educational attainment at baseline. The number of early initiators for each subsample are: 7,011 (overall), 3,830 (male), 3,181 (female), 2,781 (age < 50), 4,230 (age ≥ 50), 2,700 (no college education), and 4,074 (some college or more). These heterogeneity subsamples are created after performing the overall matching procedure. The estimates are qualitatively similar when matching after creating separate heterogeneity subsamples. 95% confidence intervals constructed from heteroskedastic standard errors clustered at the individual-level are displayed.

C Wegovy Initiation for Weight Management

This appendix estimates the labor market impacts of Wegovy initiation. Our main analysis focuses on Ozempic initiation, which is approved for diabetes management in Denmark rather than for weight management. Accordingly, 84 percent of individuals in our main analysis sample are diabetic at baseline. Wegovy provides a complementary treatment margin: in Denmark, Wegovy has been available since December 2022 and is the only GLP-1 product approved specifically for weight management (Medicin.dk, 2026b). This treatment margin is also of policy importance, as GLP-1 use for weight management has expanded rapidly in recent years and is likely to account for an increasing share of future GLP-1 utilization.

Because Wegovy became available in Denmark only in December 2022, the available follow-up period is too short to implement our baseline design, which matches initiators treated 16 quarters apart. We therefore use an alternative stacked difference-in-differences design following Diamond (2026)—who studies GLP-1 initiation for weight management in the U.S.—by comparing each initiation cohort to all later initiators observed before their own initiation.

Sample Definition. Our treatment group consists of individuals who initiate Wegovy between December 2022 and December 2023 and have no prior Ozempic use. This restriction isolates new Wegovy initiators from individuals switching from earlier semaglutide treatment, so that initiation more closely captures the start of GLP-1 treatment for weight management and ensures that Wegovy initiation treatment effects are not contaminated by the causal impacts of prior GLP-1s like Ozempic.

We begin with 107,589 Wegovy initiators during this period. We further restrict the sample to men and women aged 30–59 whom we observe for at least four pre-initiation quarters. This results in a final analysis sample of 67,736 initiators. 70% of the sample are women and 9.1% are diabetic at baseline.

Matching Procedure. Following Diamond (2026), we construct a stacked difference-in-differences design in which individuals initiating Wegovy in a given quarter are compared to individuals initiating Wegovy in later quarters. Later initiators serve as controls only in quarters before their own Wegovy initiation.

We adapt the matching procedure to the Danish register data. The study focuses on women and exactly matches individuals by partnership status and whether they are employed or on paid leave. Because our Wegovy analysis includes both men and women, we additionally exact match on sex. In the Danish registers, we define partnership as being married or in a registered partnership, and we define labor market attachment using whether an individual is in the labor force.

For each initiation cohort, we measure baseline characteristics prior to Wegovy initiation—using the quarter prior to initiation for most variables and November of the prior year for labor market variables—and form exact-match cells based on sex, partnership status, and labor market attachment. Within each exact-match cell, we estimate propensity scores and re-weight later-initiating controls using propensity score odds weights. The covariates are chosen to capture the same broad dimensions as her survey-based controls, subject to availability in the Danish registers, and are reported in Table C.1.

Stacked Difference-in-Differences Specification. Let G_i denote the quarter in which individual i initiates Wegovy. For each initiation cohort g, we create a cohort-specific stack containing individuals with $G_i = g$ and individuals with $G_i > g$. Later initiators are included as controls only in quarters $t < G_i$. We estimate event-study specifications of the form:

$$y_{igt} = \alpha_{ig} + \lambda_{gt} + \sum_{e \neq -1} \beta_e \mathbf{1}\{G_i = g\}\mathbf{1}\{t - g = e\} + \varepsilon_{igt}, \tag{2}$$

where α_{ig} are individual-by-stack fixed effects and λ_{gt} are initiation-cohort-by-calendar-quarter fixed effects. The term $\mathbf{1}\{G_i = g\}$ indicates membership in the treated group within stack g. The omitted event-time period is the quarter before Wegovy initiation, $e = -1$. Observations are weighted using the exact-match and propensity score weights described above. Heteroskedasticity-robust standard errors are clustered at the individual level.

The identifying comparison is between Wegovy initiators in cohort g and otherwise similar individuals who initiate Wegovy later but have not yet initiated by calendar quarter t. Because our control group consists

only of later Wegovy initiators, the available post-treatment horizon is limited by the distance between the first and last initiation cohorts. In our sample, initiation cohorts run from 2022Q4 through 2023Q4, so later-initiator controls provide support for only the first three post-initiation quarters.

Results. We estimate effects on the same outcomes as in the main analysis: long-term sickness leave, out-of-labor-force status, employment, and log total income. By post-initiation quarter +3, we estimate a 1 pp reduction in long-term sickness leave. This estimate is remarkably similar in magnitude to our baseline estimates for Ozempic initiators in 2018–2019. We do not find significant improvements in employment status or total income. If anything, the point estimates imply small insignificant reductions in employment and income. We interpret these estimates with caution because these outcomes exhibit modest pre-trends leading up to Wegovy initiation. We also repeat the analysis separately by sex. The estimated effects are similar to the full sample estimates, and we do not find meaningful differences between men and women.

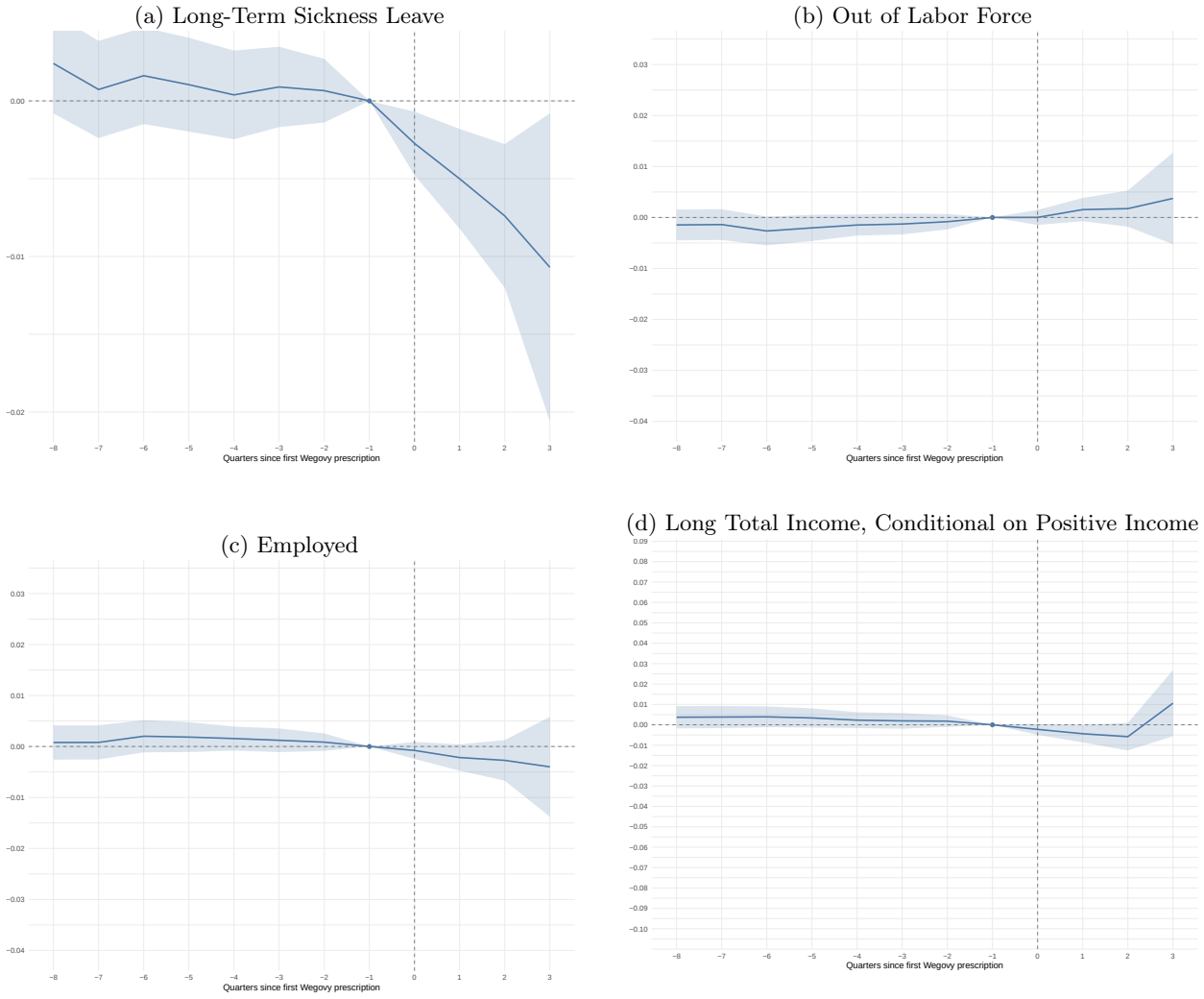
This Wegovy analysis complements our main Ozempic initiation design by focusing on the GLP-1 product approved for weight management in Denmark. The exercise differs from Diamond (2026)'s in three important ways. First, we use registry-based Wegovy initiation as a proxy for GLP-1 use for weight loss, whereas she observes self-reported GLP-1 use for weight loss. Second, our baseline covariates are administrative proxies for survey-based health and socioeconomic measures. Third, our comparison group is limited to later Wegovy initiators, not including interested never-users as controls. More broadly, Denmark and the United States are distinct institutional settings, and our results are not intended as a replication of Diamond (2026). A promising avenue for future research is to understand how institutional differences shape GLP-1 initiation and the mechanisms through which treatment affects labor market outcomes, including health, productivity, discrimination, and barriers to work.

Table C.1: Matching Variables in Diamond (2026) and Our Wegovy Analysis

	Diamond (2026)	Our Analysis
Exact match:		
Sex	—	Sex
Partnership	Partnered	Married or registered partnership
Labor-market attachment	Employed or on paid leave	In labor force
Propensity score reweighting:		
Demographics	Race	First or second generation immigrant
Body weight	BMI	Obesity diagnosis
Diabetes	Diabetes status	Diabetic diagnosis or diabetes drug use
General health	Self-rated health	Number of GP visits, specialist visits, cardiovascular drug use
Mental health	Depression score	Antidepressant use
Work-limiting health	Whether health limits work	Disability insurance
Life satisfaction	Life satisfaction	—
Income	Household income	Individual total income
Cohort fixed effect	Cohort fixed effect	Cohort fixed effect

Notes: The table compares the variables used in our matching procedure with those used in Diamond (2026). Differences in variable definitions reflect the fact that our study uses Danish administrative registers instead of U.S. survey data. Diamond (2026)'s primary sample is restricted to women, although she also reports results separately by sex; in our pooled sample, we therefore include sex as an additional exact-match variable. The vast majority of individuals in the labor force who are not employed will receive some paid benefits in Denmark. All variables are taken at baseline in the quarter prior to initiation when available or the November in the year prior to initiation for labor market variables. Within each exact-match cell, later-initiating controls are reweighted using propensity score odds weights.

Figure C.1: Main Outcomes Following Wegovy Initiation



Notes: The figure reports event study estimates of Equation 2 on our four main outcomes: long-term sickness leave, employment, out-of-labor-force status, and log total income. Each panel plots coefficients from the stacked difference-in-differences specification described in Appendix C. The omitted event time period is the quarter before Wegovy initiation. Later Wegovy initiators serve as controls only in quarters before their own initiation. Estimates are weighted using the exact-match and propensity score odds weights described in Table C.1. 95% confidence intervals constructed from heteroskedastic standard errors clustered at the individual-level are displayed.