From Screen to Script: Media Shocks and the Margins of Health Care Utilization

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Abstract

We study how salient information shocks affect health care utilization when symptoms are diagnostically ambiguous and access to treatment requires a physician consultation. Using two nationally broadcast menopause documentaries in the United Kingdom and a difference-in-regression-discontinuity-in-time design, we find the first documentary increases HRT prescribing by 28 percent among menopausal-age women, concentrated among first-time users. This response operates entirely through expanded entry into condition-relevant care: we detect no change in treatment choice conditional on consultation and no substitution across related treatments. Entry responses are markedly weaker in more deprived areas, widening preexisting utilization gradients despite uniform prices, eligibility, and clinical guidelines.

JEL codes: I11, I12, D83, C21

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1 Introduction

Information and media exposure can alter economic behavior by shaping beliefs, shifting attention, and changing how individuals interpret available choices (DellaVigna and Gentzkow, 2010; La Ferrara et al., 2012). In health contexts, prominent releases of scientific evidence and public health communications have been linked to changes in screening, testing, and treatment use (Kenkel, 1991; Cutler and Glaeser, 2005; Oster et al., 2013; Einav et al., 2020). Yet obtaining treatment is rarely a single decision. In many institutional settings, access to treatment is mediated through a physician consultation, so observed prescribing reflects a sequence of choices. Without separating these margins, observed changes in treatment conflate whether individuals seek condition-relevant attention with what happens once they do.

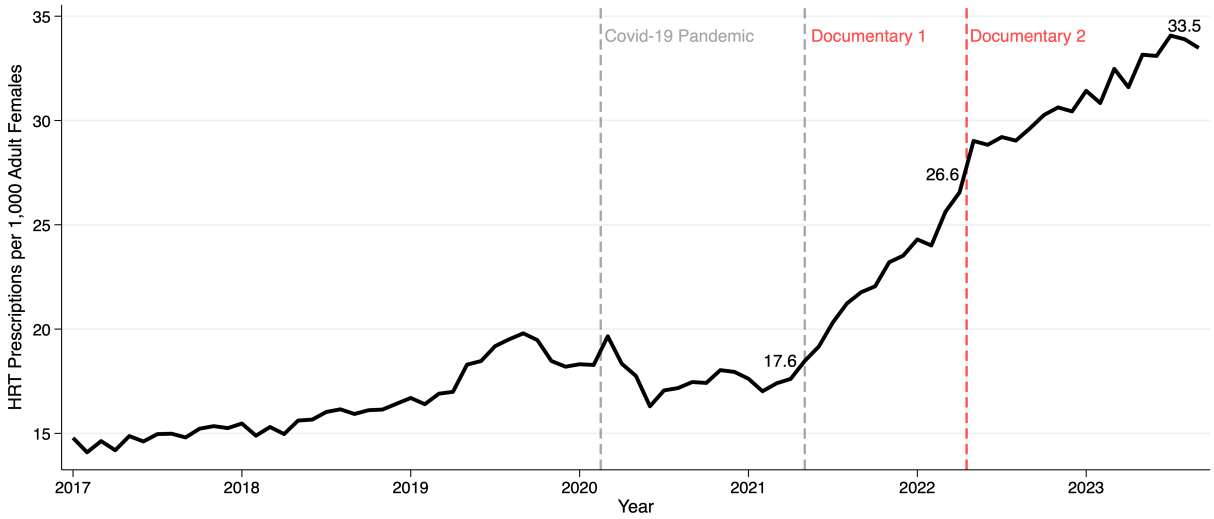
This paper studies how nationally broadcast documentaries on menopause in the United Kingdom affected health care utilization in such a sequential environment. The broadcasts increased both the visibility of menopause as a diagnostic category and the information available about hormone replacement therapy (HRT). Menopause-related symptoms are often diffuse and overlap with other common conditions, and access to HRT requires a physician consultation within the National Health Service. This setting provides a sharp test of whether passive media exposure can shift prescribing when supply-side conditions are held constant. It also permits a further question: does an observed increase in HRT prescribing reflect changed treatment preferences or provider behavior, or simply more women seeking menopause-relevant consultation? Identifying which margin of this sequence drove the increase is central to understanding how the documentaries affected behavior. While menopause provides a particularly clear setting for this analysis, these structural features – diagnostically ambiguous symptoms and gatekept access to treatment – characterize a broad class of health conditions.

To motivate the scale and timing of the prescribing responses to the documentaries, in Figure 1 we present the aggregate time series of HRT prescriptions in England from 2017 onward. After a prolonged period of relative stability, prescribing increases sharply from mid–2021, with a clear inflection at the time of the first documentary. This surge has been widely discussed in the UK press as the "*Davina Effect*".[1]

Whether the broadcasts caused this increase is a question the aggregate time series cannot answer. To estimate the causal effect of the documentaries on prescribing and to identify where

[1]See, for example, *The Guardian* (26 April 2022), which describes the post-broadcast surge in demand for HRT as the "Davina effect". The article reports on rising HRT prescribing and related supply pressures (`https://www.theguardian.com/society/2022/apr/26/manufacturers-struggle-to-keep-up-with-soaring-demand-for-hrt`).

Figure 1: The "Davina Effect": Aggregate HRT Prescribing in England



Notes: Time series data on HRT prescribing rates (per 1,000) for adult women in England. Values are smoothed using a backward-looking three-month moving average. Source: CPRD Aurum, January 2017-September 2023.

in this sequence the response occurs, we implement a difference-in-regression-discontinuity-in-time (DRD) design that exploits biological variation in menopause risk across age groups. The running variable is calendar time, and identification comes from discontinuous changes at the broadcast dates. Women aged 45–54 at the time of broadcast constitute a biologically relevant group for whom menopause-related symptoms are common, while women aged 35–44 serve as a proximate comparison cohort. The younger group is close in age and exposed to the same time-varying shocks, but substantially less likely to experience menopause-related symptoms. Under standard DRD assumptions, differencing discontinuities across these age groups isolates the effect of the documentaries on menopausal-age women.

We combine this design with comprehensive administrative data from English primary care records observed at monthly frequency. The data allow us to observe not only prescriptions for hormone replacement therapy (HRT), but also physician-led consultations in which menopause or HRT is recorded. This feature is central to the analysis. In the NHS, access to HRT requires a physician consultation, so prescribing is conditional on that consultation. The data therefore permit us to distinguish between changes in overall HRT prescribing and changes in menopause-related consultations that precede treatment decisions.

This distinction allows us to decompose prescribing into two margins: entry into menopause-relevant care and treatment decisions conditional on consultation. By separately estimating discontinuities in consultations and in HRT prescribing conditional on such consultations, we are able to assess whether documentary-induced changes in behavior reflect more women seeking

condition-relevant consultations or altered treatment decisions once consultation occurs.

We find that both documentaries generate large, immediate increases in HRT prescribing among menopausal-age women, relative to younger women. These increases take the form of sharp discontinuities at the months of broadcast, over and above contemporaneous responses common across age groups. Following the first documentary, HRT prescribing among women aged 45–54 rises by 28 percent relative to baseline levels, with the increase concentrated among women receiving HRT for the first time. Effects following the second documentary are smaller but remain economically meaningful. These are substantial behavioral responses to passive media exposure.

We then show that these increases operate entirely through expanded entry into menopause-relevant care. Both documentaries induce sharp rises in physician-led consultations in which menopause or HRT is recorded. By contrast, we detect no change in HRT prescribing conditional on such consultations. Baseline prescribing rates conditional on consultation are already high, and treatment decisions do not shift within consultations. The documentaries raise the chance of making it to the consulting room, not what happens inside it.

Consistent with this interpretation, we find no evidence of substitution across related medications within menopause-related consultations. Prescribing of antidepressants, anxiolytics, migraine treatments, and other symptom-specific drugs does not change discontinuously following the documentaries.

We further document pronounced socioeconomic heterogeneity in these responses. While the documentaries increase menopause-related consultations and HRT use across all areas, the effects are substantially weaker in more deprived neighborhoods. As a result, preexisting socioeconomic gradients in menopause-related care widen following the broadcasts. These patterns indicate systematic differences in how increased visibility and information translate into condition-relevant consultation.

The consistency of these patterns across two distinct broadcasts twelve months apart provides a within-study replication of our key results: the prescribing response, the margin through which it operates, and the socioeconomic gradient it produces.

Our work contributes to the literature on information and health care demand (Grossman, 1972; Oster et al., 2013; Einav et al., 2020) and on the behavioral effects of mass media (DellaVigna and Gentzkow, 2010; DellaVigna and Kaplan, 2007; Enikolopov et al., 2011; La Ferrara et al., 2012; La Ferrara, 2016). We document large prescribing responses to nationally broadcast documentaries in a universal, publicly funded health care system. The scale of these responses

demonstrates that passive media exposure can meaningfully impact participation in health care settings where access to treatment is mediated through a physician consultation. That they operate entirely through the entry margin sharpens how information shocks in such environments should be interpreted: what appears as a shift in treatment need not reflect changed preferences or provider behavior, but rather a change in whether women reach the consulting room. A further implication is distributional. When the operative margin is entry, the barriers that matter are those that govern whether individuals recognize and act on condition-relevant information – barriers that are themselves socioeconomically patterned. In our setting, these barriers prove stronger in more deprived areas, so that the documentaries widen existing gradients rather than narrow them (van Doorslaer et al., 2000; Morris et al., 2005; Sutton, 2002; Moscelli et al., 2018; Marmot, 2010; Marmot and Bell, 2012).

In concurrent work, Conti et al. (2025) document large causal effects of menopause on earnings and employment in Scandinavia, and show that a Swedish television program – which aired alongside updated prescribing guidelines – expanded menopause-related care and mitigated these losses. Our setting isolates demand-side responses in the absence of accompanying policy changes and identifies the specific margin of the decision sequence through which media exposure operates.

2 Institutional Setting and Data

2.1 Hormone Replacement Therapy in England

Hormone Replacement Therapy and Menopause Hormone replacement therapy (HRT) supplies estrogen, and where clinically indicated progestogen, to treat symptoms associated with the menopausal transition and post-menopause. Menopause typically occurs in midlife and reflects a natural decline in hormone levels. Symptoms may include vasomotor disturbances (e.g., night sweats, hot flashes), sleep disruption, genitourinary symptoms, and changes in mood, although experiences vary widely across individuals (NICE, 2024).

Reflecting the heterogeneous risk-benefit profile documented in the clinical literature (MacLennan et al., 2004; Writing Group for the Women's Health Initiative Investigators, 2002; Manson et al., 2013; Gu et al., 2024), NICE recommends individualized prescribing following discussion of benefits and risks (NICE, 2024, 2025).[2] Clinical guidance was stable throughout our study

[2]The National Institute for Health and Care Excellence (NICE) is an executive non-departmental public body of the UK Department of Health and Social Care which publishes guidelines for clinical practice and the use of healthcare technologies in the National Health Service.

period, and there were no major national revisions to NICE menopause recommendations over this window. Further clinical detail is provided in Appendix B.

Despite national guidance and universal coverage, HRT prescribing varies across England. Socioeconomic differences in prescribing have been documented, with lower prescribing in more deprived areas (Hirst et al., 2025). These baseline gradients are relevant for interpreting heterogeneous responses to the documentary shocks.

Primary Care and Prescribing in England In England, HRT is predominantly obtained through the National Health Service (NHS), a tax-funded system providing universal coverage. Virtually the entire resident population is registered with an NHS general practice (NHS England Digital, 2026). General practitioners (GPs) act as gatekeepers to specialist and hospital care, and access to HRT is typically mediated through a GP consultation.[3]

Prescription medications are subject to a fixed per-item charge, though the majority of items are dispensed free of charge (NHS Business Services Authority, 2026; Department of Health & Social Care, 2025).

2.2 The Davina McCall Documentaries

During 2021 and 2022, two high-profile documentaries on menopause were broadcast and presented by Davina McCall.[4] Both aired on Channel 4, a publicly owned but commercially funded public service broadcaster with near-universal reach.[5] Prime-time broadcasts on Channel 4 therefore constitute nationally disseminated information shocks rather than targeted interventions (Jermyn, 2025).

The first documentary, *Davina McCall: Sex, Myths and the Menopause* (Sands, 2021), aired on 12 May 2021. It focused on raising awareness of menopausal symptoms and treatment options, combining personal testimony with expert commentary (Jermyn, 2025). Channel 4 reported that the broadcast reached 2.5 million viewers, including 14.8% of women aged 45–54 (Channel 4, 2022b).

A follow-up documentary, *Davina McCall: Sex, Mind and the Menopause* (Pirie, 2022), aired on 2 May 2022. This program placed greater emphasis on psychological and cognitive aspects of

[3]Privately funded menopause and HRT services are available but represent a supplementary route. There is no national dataset capturing private prescribing volumes. Further detail is provided in Appendix B.

[4]Davina McCall is a long-standing British television presenter and media personality with high national name recognition.

[5]Channel 4 reported an average monthly reach of approximately 50 million individuals during 2021–2022, corresponding to around 83% of the UK population (Channel 4, 2022a). Live linear broadcasts accounted for the majority of viewing (Channel 4, 2022a; Ofcom, 2025).

menopause and reinforced earlier messaging (Jermyn, 2025). Together, the broadcasts provide two sharp national shocks to menopause-related salience and information at clearly defined calendar dates.

We use Google Trends search-term data for "menopause" and "HRT" in England to validate the timing of public attention shocks around the documentary broadcasts. Appendix Figure A1 shows sharp spikes in both search terms at the time of each documentary.

2.3 Data and Summary Statistics

We use data from the Clinical Practice Research Datalink (CPRD) Aurum database (Wolf et al., 2019). CPRD Aurum contains anonymized electronic health record data from English GP practices using the EMIS Health system. As of the December 2023 release, 1,589 practices were contributing data, covering approximately 23.9 percent of the UK population (Clinical Practice Research Datalink, 2023). CPRD Aurum is broadly representative of the English population with respect to age, sex, geography, and area-level deprivation (Wolf et al., 2019).

We construct a patient-month panel using registration and de-registration dates to determine periods of observability. We restrict to women and define treatment and control cohorts using recorded year of birth.

Our primary outcome is an indicator for HRT prescribing at the patient-month level. We also construct measures distinguishing first prescriptions from follow-up prescriptions using a 24-month look-back window. In addition, we define an indicator for physician-led consultations in which menopause or HRT is recorded. Non-HRT prescribing outcomes are defined using British National Formulary (BNF) classifications. Full construction details are provided in Appendix B.

Socioeconomic disadvantage is measured using linked 2019 Index of Multiple Deprivation (IMD) data at the patient level (Ministry of Housing, Communities & Local Government, 2019).

Summary Statistics Summary statistics for treatment and control women in the three months prior to the first documentary are presented in Appendix Table A1.

3 Conceptual Framework

3.1 Diagnostic Ambiguity and Entry into Care

Consider an individual i experiencing symptoms that are not uniquely diagnostic. Many menopause symptoms – such as sleep disturbance, anxiety, low mood, and migraines – are consistent with

multiple underlying conditions. In such environments, individuals face diagnostic ambiguity: symptoms must be interpreted before care is sought.

We denote entry into menopause-relevant primary care by

$$E_i = \mathbb{1}[\text{individual } i \text{ enters menopause-relevant primary care}].$$

Entry corresponds to a process of *diagnostic framing*. Menopause must enter the individual's diagnostic consideration set and be interpreted as a condition warranting medical attention. When menopause is not salient, symptoms may be normalized, attributed to alternative causes, or left untreated. When menopause becomes salient, the same symptoms may be reinterpreted as menopause-related, increasing the likelihood of seeking menopause-specific care. Salience therefore operates primarily through the entry margin.

3.2 Treatment Decisions Within Care

Conditional on entry, treatment decisions are made within a consultation. We denote prescribing of HRT medication by:

$$T_i = \mathbb{1}[i \text{ receives HRT} \mid E_i = 1]\,.$$

This decision reflects clinical guidance, contraindications, individual risk profiles, preferences, and provider behavior. In the institutional context we study here, access to primary care is universal and prescribing is governed by national clinical guidelines.

Observed prescribing can therefore be written as

$$Y_i = E_i \times T_i.$$

This decomposition applies generally to settings in which access to treatment is mediated through consultation.

3.3 Empirical Implications

Which margin responds to an information shock depends on two observable features of the institutional environment: the degree of clinical consensus governing treatment conditional on entry, and the distribution of barriers to entry across the population.

When Will the Intensive Margin Respond? An information shock can shift T_i if it changes treatment decisions within consultations – for instance, by updating beliefs about treatment efficacy or safety, or by altering patient advocacy or provider prescribing norms. The scope for such a response depends on how much residual uncertainty governs the treatment decision at the point of care. When clinical consensus on treatment is weak, conditional prescribing rates are low, or guidelines are in flux, new information can substantively alter treatment choice. Conversely, when prescribing conditional on consultation is governed by established guidelines and conditional prescribing rates are already high, there is limited scope for an information shock to move T_i. In our setting, NICE guidance on HRT was stable throughout the study period and baseline conditional prescribing rates among women with menopause-related consultations exceed 65 percent (Table A1). These features imply a setting in which the intensive margin is near-saturated and the primary scope for an information shock to raise prescribing is through expanded entry.

When Will Entry Responses Be Socioeconomically Unequal? If the operative margin is entry, then the magnitude of the response depends on the barriers governing whether individuals recognize symptoms as condition-relevant and act on that recognition. These barriers are themselves socioeconomically patterned: baseline socioeconomic gradients in both menopause-related consultations and HRT prescribing are evident in our data (Appendix Figure A2). An untargeted national broadcast reaches all socioeconomic groups with approximately equal intensity, but diagnostic reframing is more readily achieved among individuals whose preexisting barriers to entry are lower. Entry responses to a uniform information shock will therefore be larger in less-deprived areas, steepening preexisting socioeconomic gradients in condition-relevant care rather than narrowing them. Because salience and the capacity to act on it enter multiplicatively, increasing the intensity of the information shock cannot flatten the gradient as long as the underlying capacity gap persists. This implication is non-trivial: if the information shock were to operate on T_i, the distributional pattern would be attenuated by the uniform clinical guidelines governing prescribing decisions within consultations.

These implications are testable. We examine them in Sections 5.2–5.4.

4 Empirical Specification

In our setting, observed HRT prescribing reflects two distinct margins: entry into menopause-relevant care and treatment conditional on entry. We observe these margins at the individual-month level. Let Y_{im} denote an indicator for whether individual i is prescribed HRT in month m. As set out in the conceptual framework, $Y_{im} = E_{im} \times T_{im}$, where E_{im} indicates entry into menopause-relevant primary care and T_{im} indicates receipt of HRT conditional on entry.

Our empirical objective is to estimate the causal effect of the documentary broadcasts on HRT prescribing and to identify where in the care pathway this response occurs: through entry into menopause-relevant care (E_{im}), treatment conditional on entry (T_{im}), or both.

The unit of observation in our data is the individual-month, with i indexing individuals and m indexing calendar months. We avoid additional indexing for the two documentaries in order to keep the notation lean; each equation is relevant for both documentaries. For each documentary aired in broadcast month c, we define the running variable as

$$Z_m = m - c\,,$$

such that $Z_m = 0$ corresponds to the documentary month. We define the post-documentary indicator as $Post_m = 1[m \geq c]$.

Our treatment-group assignment rule is informed by the medical literature on menopause. Women aged 45–54 at the time of each broadcast constitute the treatment group ($D_i = 1$), and a biologically proximate cohort serves as the control group – those aged 35–44 ($D_i = 0$). The younger group is close in age and exposed to the same time-varying shocks, but substantially less likely to experience menopause-related symptoms.

Using the potential outcomes framework as our basis, we respectively denote untreated and treated potential outcomes as $Y_{im}(0)$ and $Y_{im}(1)$. For each group $d \in \{0, 1\}$, we then define the group-specific regression discontinuity estimand as the jump at the cutoff:

$$\delta_d = \lim_{Z \downarrow 0} E[Y_{im}(1) \mid D_i = d, Z_m = Z] - \lim_{Z \uparrow 0} E[Y_{im}(0) \mid D_i = d, Z_m = Z]\,.$$

The difference-in-discontinuities estimand can then be written as

$$\tau = \delta_1 - \delta_0\,.$$

The DRD estimand, τ, captures the extent to which the documentary induces a discrete change in HRT prescribing in the treatment group relative to the control group at the time of broadcast. In light of the decomposition above, any estimated τ reflects a composite of shifts in entry into menopause-relevant care, treatment conditional on entry, or both. We estimate τ separately for each documentary by redefining the cutoff month c and restricting the sample to a local window around the corresponding broadcast date.[6]

4.1 Estimating Equation

To estimate τ, we implement a difference-in-regression-discontinuity-in-time (DRD) design using a local linear specification. For a given documentary cutoff c, we estimate the following regression equation:

$$\begin{aligned} Y_{im} = &\alpha + \tau\,(D_i \times Post_m) + \beta_1 Post_m + \beta_2 D_i + \gamma_1 Z_m + \gamma_2\,(Z_m \times Post_m) \\ &+ \gamma_3\,(Z_m \times D_i) + \gamma_4\,(Z_m \times Post_m \times D_i) + \varepsilon_{im}\,. \end{aligned} \tag{1}$$

The coefficient τ captures the difference in the discontinuity at the cutoff between the treatment and control groups and is the parameter of interest. The specification allows for separate linear trends in month-time on either side of the cutoff. These trends can differ flexibly by group. The combination of sharp temporal discontinuities at the broadcast dates with a biologically proximate control cohort guards against confounding by contemporaneous aggregate shocks, including post-pandemic supply chain disruptions that affected medication availability. Estimation is conducted using observations within a symmetric window around the cutoff, $|Z_m| \leq h$, where h denotes the chosen bandwidth. The error term is ε_{im}. We use Eicker–Huber–White standard errors throughout.[7]

We apply this same specification to three outcomes. First, we estimate the effect of the documentaries on overall HRT prescribing, Y_{im}. Second, we estimate the effect on entry into menopause-relevant care, E_{im}, defined as an indicator for a physician-led consultation in which menopause or HRT is recorded. Third, we estimate the effect on treatment conditional on entry by estimating the same DRD specification within the subsample of individual-months for which

[6] Given our age-based group definitions, there is large but not perfect overlap in our treated and control groups across the two documentaries. For instance, a woman aged 44 would be in the control group for Documentary 1 but in the treatment group for Documentary 2.

[7] Our running variable is discrete at the monthly level, yielding seven support points at the baseline bandwidth of $h = 3$. Kolešár and Rothe (2018) develop honest confidence intervals for regression discontinuity designs with discrete running variables. Given that our core estimates have t-statistics exceeding 20, our conclusions are robust to any plausible widening of confidence intervals under their framework.

$E_{im} = 1$.

The intensive-margin estimand conditions on a post-treatment variable – entry into menopause-relevant care – raising a concern analogous to the bad-control problem (Angrist and Pischke, 2009): since the documentaries induce entry, the composition of the $\{E_{im} = 1\}$ subsample shifts discontinuously at $Z_m = 0$, and the group-specific discontinuity in T_{im} conflates a treatment effect with a composition effect from documentary-induced new entrants. The DRD resolves this by differencing across age cohorts: under the conditions set out in Appendix D, the composition effect cancels in the DRD, and the estimator recovers the treatment effect on T_{im} for women who would have entered menopause-relevant care regardless of the broadcasts. A zero estimate therefore reflects the absence of an intensive-margin response rather than an artifact of conditioning.

We follow the approach of Calonico et al. (2014) to calculate the optimal bandwidth for HRT prescribing – our key outcome variable – doing so separately by group and documentary, using a 1% random sample of the data to accommodate the computational demands of the bandwidth selection procedure at the scale of the full sample. Based on this exercise, for both documentaries, we use a bandwidth of $h = 3$ months. We explore the sensitivity of our key findings to alternative bandwidths. Our results remain substantively unchanged with alternative bandwidths.

4.2 Identifying Assumptions

Identification of τ relies on a set of core assumptions.

Assumption 1: Group-Specific Local Regularity Around the Cutoff. For each group $d \in \{0, 1\}$, the conditional expectation of untreated potential outcomes,

$$E[Y_{im}(0) \mid D_i = d, Z_m = Z],$$

is locally smooth in Z_m on each side of the cutoff in a neighborhood of $Z_m = 0$, and the left- and right-hand limits at $Z_m = 0$ exist. This ensures that group-specific regression discontinuity estimands are well-defined and allows for the possibility of a discontinuity in untreated outcomes at the cutoff. We provide support for this condition using by-group RD graphs around each documentary month (Appendix Figure B1).

Assumption 2: Common Discontinuity in Untreated Potential Outcomes Across Groups. We define the untreated discontinuity at the cutoff for group $d \in \{0, 1\}$ as

$$\delta_d^{(0)} = \lim_{Z \downarrow 0} E[Y_{im}(0) \mid D_i = d, Z_m = Z] - \lim_{Z \uparrow 0} E[Y_{im}(0) \mid D_i = d, Z_m = Z].$$

The DRD restriction is that the untreated discontinuity is common across groups:

$$\delta_1^{(0)} = \delta_0^{(0)}.$$

This condition replaces the continuity requirement of a standard RDD and ensures that differencing the group-specific discontinuities removes any non-documentary-related time shock occurring at the cutoff. This assumption cannot be tested directly, but we provide supporting evidence from two complementary exercises: DRD estimates for predetermined patient and practice characteristics (Appendix Table B1), and DRD estimates for a set of placebo prescription outcomes (Appendix Table B2). The absence of differential discontinuities in these covariates and placebo outcomes mitigates concerns that our core results are driven by age-specific time effects or confounding shocks.

Assumption 3: Stability of Sample Composition and Outcome Measurement at the Cutoff. There are no discontinuous changes at c in the composition of observed individuals or in outcome measurement that differentially affect the treatment and control groups. In particular, sample inclusion, individual characteristics, and the mapping from underlying HRT need or preferences to the observed prescribing outcome evolve smoothly through the cutoff or change in ways that are common across groups. We present density diagnostics around both cutoffs using a discrete-running-variable variant of the McCrary density test (Frandsen, 2017) and cannot reject the null of no change in density for any group-documentary pair (Appendix Figure C2).

5 Results

We present our results in four parts: the overall prescribing response, the decomposition into entry and treatment margins, spillovers across related medications, and heterogeneity by socioeconomic deprivation.

5.1 HRT Prescribing Responses to the Documentaries

Table 1 presents DRD estimates for each documentary across a core set of HRT prescribing outcomes.

Table 1: DRD Estimates – HRT Prescribing

	(1)	(2)	(3)	(4)	(5)	(6)
	Documentary 1			**Documentary 2**		
	HRT	HRT: First Prescription	HRT: Follow-up	HRT	HRT: First Prescription	HRT: Follow-up
DRD	.00952***	.00693***	.00258***	.00558***	.00516***	.00042
	(.00045)	(.00013)	(.000434)	(.00054)	(.000153)	(.000523)
$\overline{Y}_{\text{Pre}}$	.0343	.00197	.0323	.0518	.00383	.0479
DRD / $\overline{Y}_{\text{Pre}}$	.278***	3.52***	.08***	.108***	1.35***	.00877
	(.0131)	(.0661)	(.0134)	(.0104)	(.0401)	(.0109)
Adjusted R^2	.0523	.00446	.0489	.0784	.00455	.0741
Observations	14,848,153	14,848,153	14,848,153	15,061,063	15,061,063	15,061,063

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Eicker-Huber-White standard errors in parentheses. Practice fixed effects and age fixed effects are included in all specifications. Both documentary samples are based on a 3 month window around the respective documentary month. We use the approach of Calonico et al. (2014) to calculate optimal bandwidths. In this setting, time (months) is our running variable. All specifications are based on a polynomial of order one in time. Source: CPRD Aurum.

The results in Column 1 highlight an economically meaningful and statistically significant response of treatment group women, relative to those in the control group, in response to the first documentary. HRT prescriptions increase by 0.95 percentage points, from a baseline of 3.4 percentage points. In proportional terms, this is an increase of HRT prescribing of 28%. In Columns 2 and 3, we make use of the panel element of our patient-level data, decomposing the HRT prescribing response into those taking HRT for the first-time (based on a 24 month prescribing history) and those with follow-up or repeat HRT prescriptions. This set of results show that the increase we document in Column 1 is driven primarily by women taking HRT medication for the first-time (Column 2) – first-time HRT prescriptions account for 73% of the increase in HRT prescriptions overall. We additionally document a discrete increase in repeat HRT prescriptions (Column 3).

In Columns 4–6, we present corresponding estimates for the second documentary. The qualitative pattern replicates: HRT prescribing increases discretely among treated women relative to controls, and the response is again concentrated among first-time users. Point estimates are more muted – 0.56 percentage points, consistent with a second shock arriving after salience has already risen – and follow-up prescribing shows no discrete change. That first-time prescribing

drives the entire effect for both documentaries strengthens the interpretation that the broadcasts operated by drawing new women into menopause-relevant care.

5.2 Behavioral Margins: Consultations and Subsequent Prescribing

The estimates we present in Table 1 establish a discrete increase in HRT prescribing among menopause-relevant women in response to both documentaries. In this section, we decompose this response into changes in menopause-related consultations and changes in HRT prescribing conditional on a menopause-related consultation, corresponding to extensive and intensive margin effects.

Table 2: DRD Estimates – Entry and Treatment Margins

	(1)	(2)	(3)	(4)
	Documentary 1		**Documentary 2**	
	Menopause-Related Visit	HRT|MR Visit=1	Menopause-Related Visit	HRT|MR Visit=1
DRD	.00345***	.0477	.00583***	-.00762
	(.000161)	(.0334)	(.000208)	(.0244)
$\overline{Y}_{\text{Pre}}$	.00382	.664	.00692	.749
DRD / $\overline{Y}_{\text{Pre}}$	.902***	.0718	.843***	-.0102
	(.0421)	(.0502)	(.03)	(.0326)
Adjusted R^2	.00812	.0556	.0122	.0466
Observations	14,848,153	79,223	15,061,063	119,639

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Eicker-Huber-White standard errors in parentheses. Practice fixed effects and age fixed effects are included in all specifications. Both documentary samples are based on a 3 month window around the respective documentary month. We use the approach of Calonico et al. (2014) to calculate optimal bandwidths. In this setting, time (months) is our running variable. All specifications are based on a polynomial of order one in time. Source: CPRD Aurum.

The evidence we present in Table 2 highlights that for both documentaries, the key behavioral channel underpinning the increases in HRT prescribing that we document in Table 1 is the extensive margin. Both documentaries led to an immediate, statistically significant increase in menopause-related consultations (Columns 1 and 3). Neither of the documentaries led to statistically significant increases in HRT prescription conditional on a consultation, suggesting that the documentary-induced shock did not meaningfully alter behavior within menopause-relevant consultations. We additionally note that the baseline conditional means for HRT prescribing are high (66.4% and 74.9%), and increasing over time – the documentaries were only 12 months apart (Columns 2 and 4).

Such findings highlight the margin along which the two documentaries shifted behavior, leading more women of menopause age to seek a menopause-relevant consultation. This finding

is highly relevant given the backdrop of social stigmatization on the menopause transition and associated symptoms highlighted by Griffiths et al. (2013). The high rate of prescribing HRT conditional on a consultation additionally supports the notion that treatment conditional on entry is not the binding margin in HRT use. Together, these findings suggest that frictions operating prior to treatment selection are important barriers to menopause-related health-seeking behavior.

5.3 Prescribing Spillovers Within Menopause-Relevant Care

The dominance of the extensive margin that we document in Section 5.2 limits the scope for behavioral responses within menopause-relevant consultations. However, even in the absence of a shift in HRT prescribing conditional on a consultation, the documentaries could have changed the composition of treatment within menopause-relevant care, e.g., by lowering demand for symptom-specific medications used to treat overlapping symptoms. In this section, we examine whether the documentaries led to any such within-pathway spillovers to non-HRT prescribing. Specifically, we map menopause-related symptoms to BNF code-based prescribing, presenting our DRD estimates in Table 3.

Across both documentaries, and all prescription drug classes we consider here, we find no evidence of substitution across treatments within menopause-relevant consultations. Not only are the DRD point estimates typically small relative to baseline means, the signs of these estimates are not uniformly consistent across the documentaries. In addition, the standard errors are such that none of our estimates are statistically significantly different from zero.

Such findings add to our previous results – the lack of intensive margin effects is not limited to HRT prescribing, but extends to a comprehensive treatment bundle within menopause care. Linking back to our conceptual framework, these findings are noteworthy, as they provide evidence on the channels underpinning our core results. While the documentaries could plausibly have shifted behavior within consultations – for instance due to enhanced advocacy for HRT medication crowding out other medications, or supply-side responses to changes in patients' menopause-related information set – we find no such evidence for the relevance of this margin.

We thus conclude that once menopause is recognized as the organizing diagnostic frame, treatment outcomes within consultations are unmoved. We next examine how the strength of this entry-margin response varies across local socioeconomic contexts.

Table 3: DRD Estimates – Spillover Prescribing Outcomes

	(1)	(2)	(3)	(4)	(5)
	Antimigraine Drugs	CNS Stimulants and ADHD Drugs	Hypnotics and Anxiolytics	Beta Blockers	Antidepressants
A: Documentary 1					
DRD	-.00444	-.00231	-.00572	.00166	-.0272
	(.0138)	(.00184)	(.0124)	(.0128)	(.031)
$\overline{Y}_{\text{Pre}}$	.0441	.00066	.0313	.0315	.284
DRD / $\overline{Y}_{\text{Pre}}$	-.101	–3.5	-.182	.0526	-.0955
	(.312)	(2.79)	(.397)	(.407)	(.109)
Adjusted R^2	.0168	-.000083	.012	.0211	.0329
Observations	79,223	79,223	79,223	79,223	79,223
B: Documentary 2					
DRD	.00736	-.00187	.00148	.00129	-.0165
	(.0113)	(.00262)	(.00895)	(.00967)	(.0239)
$\overline{Y}_{\text{Pre}}$	.0405	.00168	.0283	.0347	.27
DRD / $\overline{Y}_{\text{Pre}}$	.182	–1.11	.0522	.0371	-.0609
	(.279)	(1.56)	(.316)	(.279)	(.0883)
Adjusted R^2	.0111	.00506	.0127	.0168	.0292
Observations	119,639	119,639	119,639	119,639	119,639
Treatment for Menopause-Relevant Symptoms:	Migraines	ADHD	Sleep Problems; Anxiety	Anxiety	Depression

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Eicker-Huber-White standard errors in parentheses. Practice fixed effects and age fixed effects are included in all specifications. Both documentary samples are based on a 3 month window around the respective documentary month. We use the approach of Calonico et al. (2014) to calculate optimal bandwidths. In this setting, time (months) is our running variable. All specifications are based on a polynomial of order one in time. Source: CPRD Aurum.

5.4 Heterogeneity by Local Socioeconomic Disadvantage

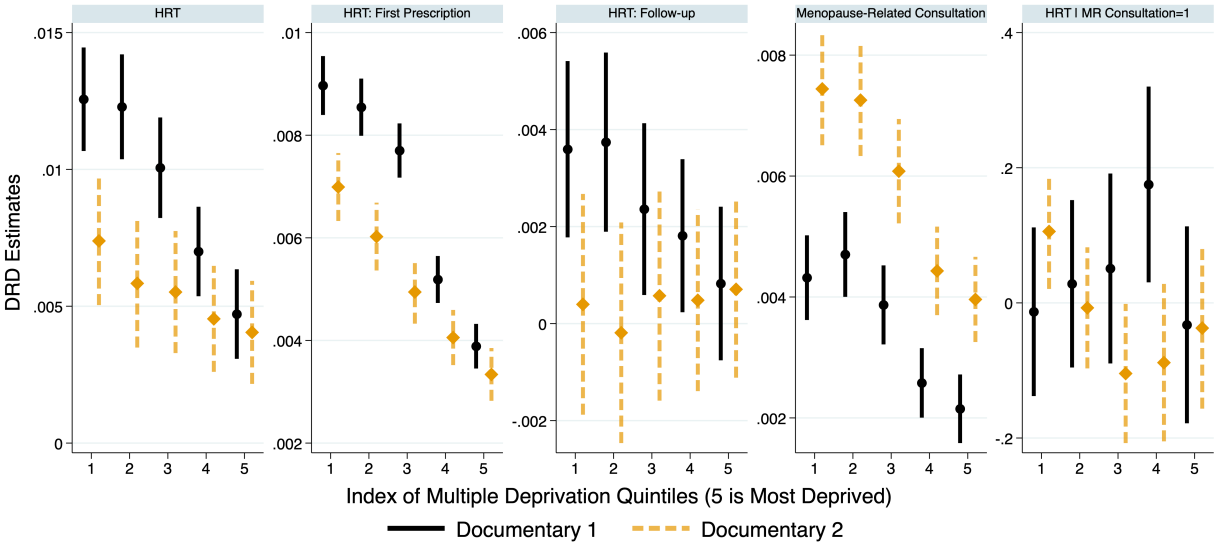
As highlighted in the previous section, the documentary-induced increase in HRT prescribing operates primarily through the extensive margin. A large body of work documents pronounced socioeconomic gradients in health-seeking behavior and realized healthcare utilization, even in settings with universal coverage (van Doorslaer et al., 2006; Marmot, 2010; Moscelli et al., 2018; Cookson et al., 2021). In this section, we examine whether socioeconomic disadvantage moderates the responses of menopause-aged women to the documentaries.

Our measure of socioeconomic disadvantage is the neighborhood Index of Multiple Deprivation (IMD) at the patient address level. The IMD captures local deprivation across seven domains, providing a comprehensive measure at a low geographic level. We use the patient's neighborhood IMD decile (2019 definition), collapsed into quintiles. At baseline, preexisting socioeconomic gradients are evident across all outcomes: women living in more deprived neighborhoods are less likely to be prescribed HRT and less likely to visit their GP for a menopause-

related consultation (Appendix Figure A2).

We present deprivation quintile-specific DRD estimates in Figure 2. Across all margins for which we find statistically significant average effects, the documentaries exacerbate preexisting socioeconomic gradients. For HRT prescribing, these gradients are steeper for the first documentary, where the DRD estimates for those in the lowest deprivation quintile are 2.7 times larger than those in the highest quintile. For menopause-related consultations, the deprivation gradient is similar (Q1:Q5 ratios of 2.0 and 1.9 respectively) for the two documentaries.

Figure 2: DRD Estimates by IMD Quintiles



Notes: We present point estimates and 90% confidence intervals for IMD quintile-specific DRD estimates. Practice fixed effects and age fixed effects are included in all specifications. Both documentary samples are based on a 3 month window around the respective documentary month. We use the approach of Calonico et al. (2014) to calculate optimal bandwidths. In this setting, time (months) is our running variable. All specifications are based on a polynomial of order one in time. Source: CPRD Aurum.

The documentaries exacerbated preexisting socioeconomic gradients, widening the gap in both access (as proxied by consultations) and HRT utilization between women residing in less- and more-deprived areas. These gradients arise against a backdrop of higher baseline levels of menopause-related health-seeking behavior in less-deprived areas, indicating unequal responsiveness of entry into menopause-relevant care to the documentary shock. The negative DRD deprivation gradients are consistent with constraints on the effectiveness of the salience and diagnostic-framing channel in more deprived areas. Consistent with Griffiths et al. (2013), social stigmatization of menopausal symptoms, together with lower baseline engagement with primary care in more deprived areas, may limit the extent to which increased menopause salience translates into care-seeking.

6 Conclusion

Our findings point to entry into condition-relevant care as a distinct and empirically important margin through which information can operate. In settings characterized by diagnostic ambiguity and intermediated access to treatment, what appears as a change in prescribing can reflect a change in whether individuals enter condition-relevant care rather than in what happens once they do.

These findings reframe how policy should respond to information-driven increases in health care demand. The principal policy response in the UK to the post-documentary surge in HRT prescribing has been to reduce out-of-pocket costs through an HRT-specific prepayment certificate. Yet our evidence indicates that the binding constraint is not cost or clinical willingness to prescribe – conditional prescribing rates exceed 65 percent – but whether women recognize their symptoms as menopause-related and present for a relevant consultation. Interventions that embed condition-relevant screening within routine primary care contacts, shifting the entry decision from patient-initiated to provider-initiated, would lower the diagnostic burden that our results identify as the operative barrier. Such approaches may be particularly important in more deprived areas, where untargeted information produces the weakest entry response.

More broadly, the conditions that produce these patterns are not specific to menopause. Entry will dominate where clinical consensus on treatment is established and conditional prescribing rates are high. Entry responses will be socioeconomically regressive where symptoms are diagnostically ambiguous and barriers to recognition are socioeconomically patterned. Conditions such as hypothyroidism and depression share both features: symptoms overlap with everyday experience, access to treatment is gatekept, and utilization gradients are well documented. Our framework predicts that information shocks in these settings would produce similarly entry-dominant and regressive responses. Conversely, in settings where clinical consensus is weaker and conditional prescribing rates are lower, the same type of shock could plausibly shift treatment decisions within consultations as well.

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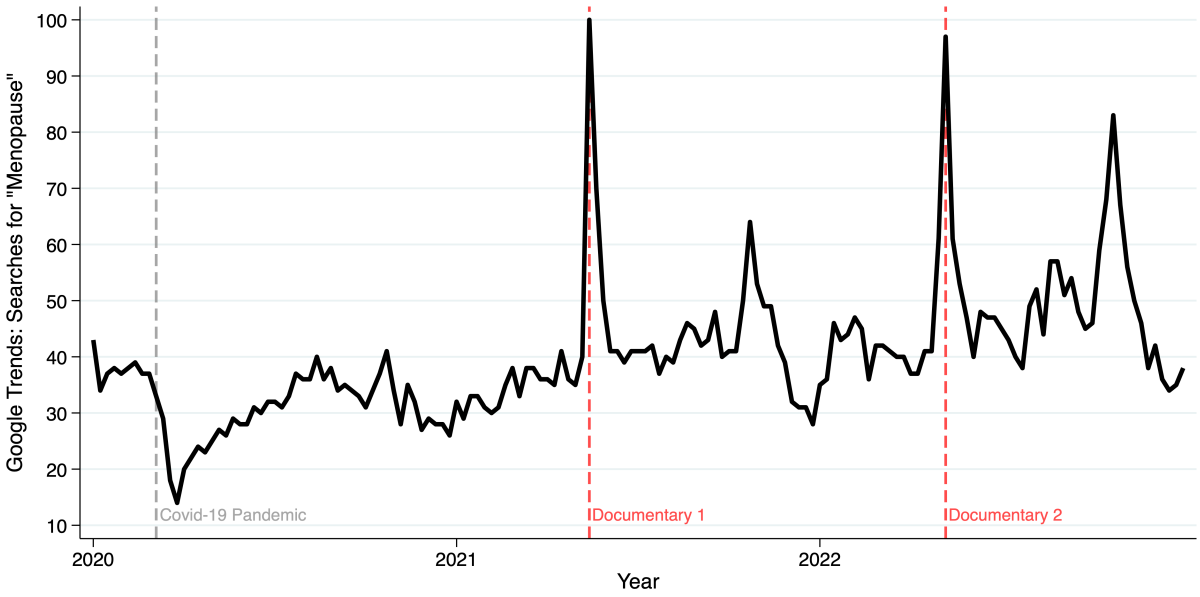
Appendix

A Auxiliary Results

A.1 Google Trends Time Series

Figure A1: Google Trends Time Series



(a) Search Term: "Menopause"

(b) Search Term: "Hormone Replacement Therapy"

Time series data on search terms for "Menopause" and "Hormone Replacement Therapy" in England. Source: Google Trends, January 2017-December 2022.

A.2 Summary Statistics

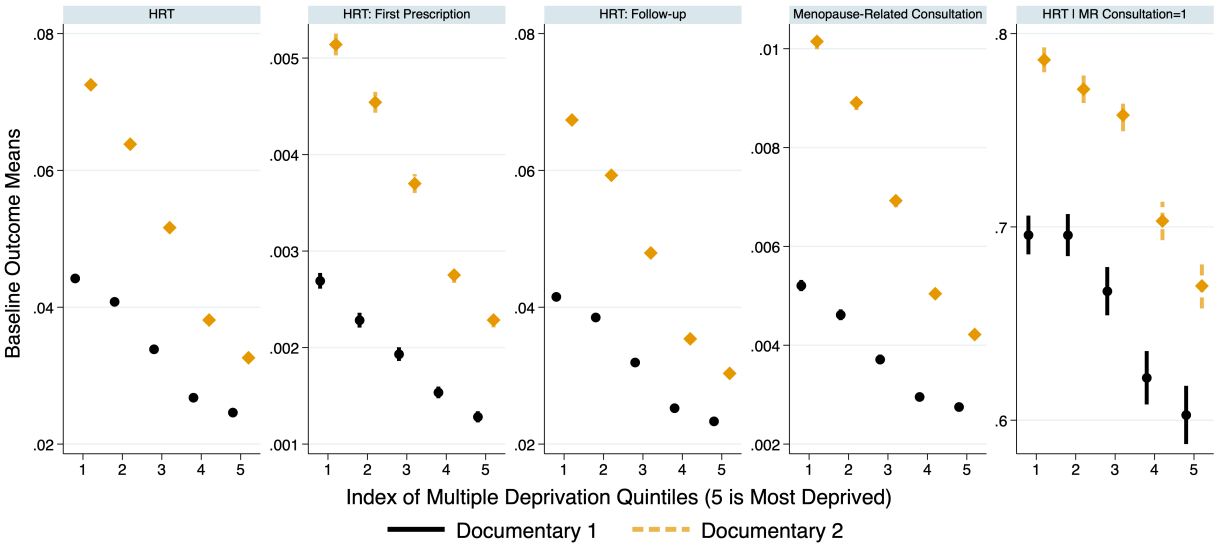
Table A1: Summary Statistics

	(1)	(2)
	Control Group (Aged 35-44)	Treatment Group (Aged 45-54)
Observations	3,285,054	3,063,761
HRT Prescription	0.006	0.064
	(0.079)	(0.245)
HRT: First Prescription	0.001	0.004
	(0.023)	(0.059)
HRT: Follow-up Prescription	0.006	0.061
	(0.076)	(0.239)
Menopause-Relevant Consultation	0.001	0.007
	(0.024)	(0.085)
Prescribing|Menopause-Relevant Consultation		
HRT	0.581	0.671
	(0.494)	(0.470)
Antimigraine Drugs	0.035	0.045
	(0.184)	(0.207)
CNS Stimulants and ADHD Drugs	0.001	0.001
	(0.023)	(0.026)
Hypnotics and Anxiolytics	0.041	0.030
	(0.199)	(0.172)
Beta Blockers	0.037	0.031
	(0.188)	(0.173)
Antidepressants	0.285	0.284
	(0.452)	(0.451)

Notes: These summary statistics are based on the sample of women in the pre-Documentary 1 period – February, March, and April 2021. Source: CPRD Aurum

A.3 Baseline Socio-economic Deprivation Gradients

Figure A2: Baseline Outcomes Means by IMD Quintiles



We present point estimates and 90% confidence intervals. Both documentary samples are based on a 3 month window around the respective documentary month. We use the approach of Calonico et al. (2014) to calculate optimal bandwidths. To establish baseline means, we use the pre-documentary window for respective documentaries. Source: CPRD Aurum.

B More Details on Institutional Setting and Data Construction

B.1 Clinical Background and Guidance

HRT is prescribed to treat menopausal symptoms including vasomotor and genitourinary symptoms (NICE, 2024). Evidence from randomized trials and observational studies demonstrates reductions in vasomotor symptoms and improvements in quality of life (MacLennan et al., 2004; Cauley et al., 2003). The WHI trials reported elevated risks for certain outcomes associated with some HRT regimens (Writing Group for the Women's Health Initiative Investigators, 2002). Subsequent analyses show that these risks vary by age at initiation, duration, and formulation (Manson et al., 2013; Gu et al., 2024; Fournier et al., 2008; Canonico et al., 2007). NICE guidance reflects this heterogeneous risk-benefit profile (NICE, 2024, 2025).

B.2 Private Prescribing

Although privately funded menopause and HRT services are available, there is no equivalent national dataset capturing private prescribing volumes, and private provision is generally considered a supplementary route for individuals who choose to self-fund rather than the primary channel of care. Access to HRT in England is therefore predominantly mediated through NHS

primary care and GP consultations.

B.3 Construction of HRT Prescription Variables

CPRD Aurum includes a drug issue dataset recording prescription date, product code, and prescription duration. Product codes are linked to a product dictionary containing text descriptions, substance names, and BNF codes.

To identify HRT medications, we implement a multi-step search strategy. We first search the substance name field for variations of the terms estradiol, estrogen, and progesterone. From the text description of these matches, we extract the first word and search for these words in the text description field across the full product dictionary, flagging any additional matches to capture branded products. We supplement this approach using a publicly available HRT code list developed in CPRD Gold (Strongman, 2019), matching on product naming conventions. The resulting list is manually reviewed to exclude medications indicated for contraception rather than HRT.

Using the final list of product codes, we construct a monthly HRT prescription indicator equal to one if a prescription covers any part of a given calendar month. We define HRT: First Prescription and HRT: Follow-up using a 24-month look-back window.

B.4 Construction of Non-HRT Prescription Variables

Non-HRT prescription outcomes are defined using British National Formulary (BNF) classifications. For each drug class, we identify relevant BNF chapters, sections, or subsections and flag products whose BNF codes begin with the corresponding digits. To address incomplete BNF coding, we supplement this with searches over substance names and text descriptions in the product dictionary. Monthly indicators equal one if an individual receives any prescription within the relevant BNF category.

B.5 Construction of Consultation Measures

CPRD Aurum includes consultation and observation datasets linked via consultation identifiers. We identify menopause-related clinical codes by searching the medical dictionary for menopause- or HRT-related terms. Observations containing these codes are linked to consultations and restricted to physician-led encounters. A patient-month is coded as having a menopause-related visit if at least one such consultation occurs in that month.

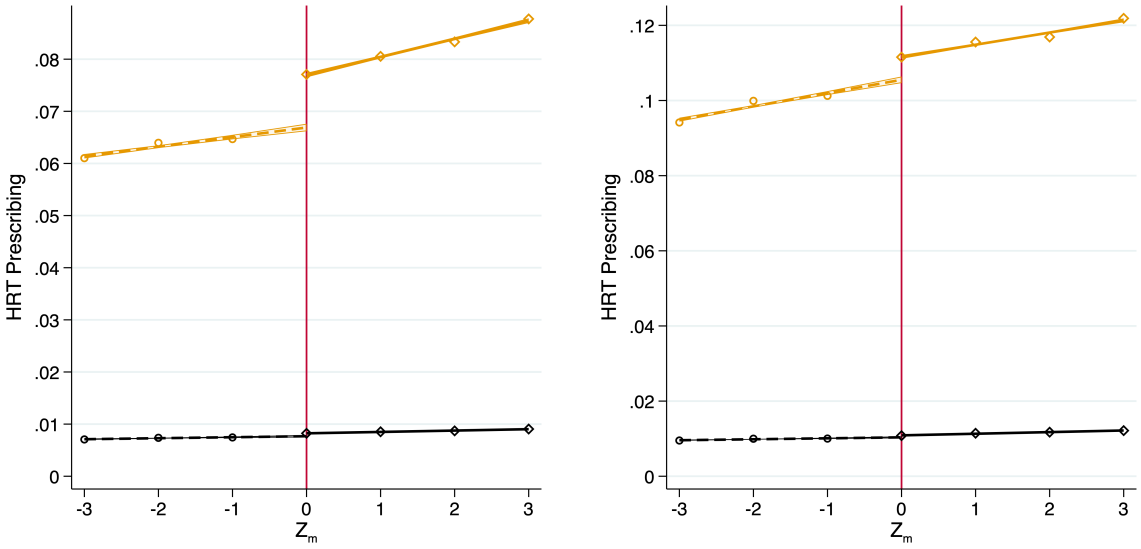
B.6 IMD Linkage

IMD 2019 data (Ministry of Housing, Communities & Local Government, 2019) are linked at the patient level using residential postcode and Lower-layer Super Output Area (LSOA). Linkage requires practice participation in the CPRD linkage scheme and a valid postcode. IMD combines seven domains of deprivation into a composite index, with lower ranks corresponding to higher deprivation.

C Support for the Identifying Assumptions

C.1 RD Graphs by Group

Figure C1: RD Graphs by Group – HRT Prescribing



(a) Documentary 1

(b) Documentary 2

Notes: Practice fixed effects and age fixed effects are included in all specifications. Both documentary samples are based on a 3 month window around the respective documentary month. We use the approach of Calonico et al. (2014) to calculate optimal bandwidths. In this setting, time (months) is our running variable. All specifications are based on a polynomial of order one in time. Source: CPRD Aurum.

C.2 Patient and Practice Characteristics

Table C1: DRD Estimates – Patient and Practice Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
	Documentary 1			**Documentary 2**		
	Age	Patient IMD Decile	Practice IMD Decile	Age	Patient IMD Decile	Practice IMD Decile
DRD	.000586	-.000496	.000552	-.00128	.000094	.00108
	(.00682)	(.00519)	(.00682)	(.0068)	(.00519)	(.00678)
$\overline{Y}_{\text{Pre}}$	44.3	5.48	5.88	44.2	5.5	5.89
DRD / $\overline{Y}_{\text{Pre}}$	.000013	-.000091	.000094	-.000029	.000017	.000183
	(.000154)	(.000947)	(.00116)	(.000154)	(.000943)	(.00115)
Adjusted R^2	.765	.522	.00188	.762	.525	.00202
Observations	14,848,153	12,494,409	14,848,153	15,061,063	12,370,880	15,061,063

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Eicker-Huber-White standard errors in parentheses. Practice fixed effects and age fixed effects are included in Patient IMD specifications. For Practice IMD Decile regressions, we remove the practice FEs. For Age regressions, we remove the age FEs. Both documentary samples are based on a 3 month window around the respective documentary month. We use the approach of Calonico et al. (2014) to calculate optimal bandwidths. In this setting, time (months) is our running variable. All specifications are based on a polynomial of order one in time. Source: CPRD Aurum.

C.3 Placebo Outcomes

To assess whether the documentaries were associated with broader changes in primary care prescribing, health-seeking behavior, or access to care, we examine placebo prescription outcomes for a set of conditions that we do not expect to have been directly affected by the documentaries. These outcomes were chosen to reflect routine primary care prescribing across a range of clinical contexts.

The placebo set includes antihypertensive medications and short-acting insulins, which capture the routine management of chronic conditions, namely long-term blood pressure control and insulin-treated diabetes. To capture acute, episodic prescribing, we include penicillins, typically prescribed as short courses for common bacterial infections, and topical antibacterial skin treatments, used for localized skin infections. Prescribing in these categories reflects temporary clinical episodes rather than long-term treatments. Finally, to capture mixed acute and chronic prescribing, we include non-steroidal anti-inflammatory drugs (NSAIDs), commonly used for pain and inflammation, and proton pump inhibitors (PPIs), which reduce stomach acid and are prescribed both short-term for indigestion and long-term for chronic gastrointestinal conditions.

Together, these outcomes span a broad range of prescribing behaviors commonly managed in primary care and are not expected to respond to either the documentary release or changes

in the treatment of menopausal symptoms. The absence of effects on these placebo outcomes provides evidence that the documentaries did not generate broader changes in primary care prescribing, health-seeking behavior, or access to care.

Table C2: DRD Estimates – Placebo Outcome Prescribing

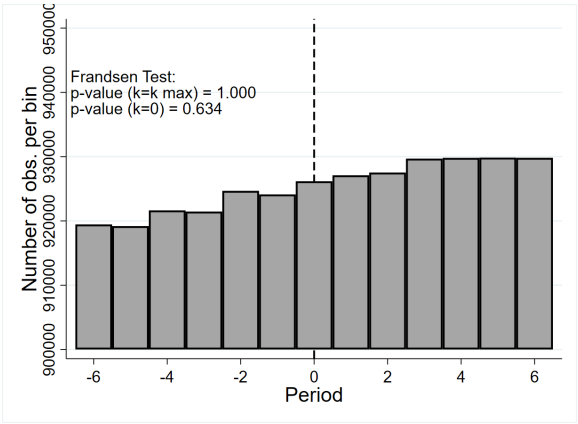
	(1)	(2)	(3)	(4)	(5)	(6)
	Anti-hypertension	Short-acting Insulin	NSAIDs	Proton Pump Inhibitors	Penicillin	Topical Antibacterial (Skin)
A: Documentary 1						
DRD	.000271	-.000094	-.000071	-.000302	.000214	-.000201
	(.000524)	(.00015)	(.000423)	(.000644)	(.000289)	(.000189)
$\overline{Y}_{\text{Pre}}$	.0496	.00385	.032	.079	.0145	.00637
DRD / $\overline{Y}_{\text{Pre}}$	.00547	-.0243	-.00222	-.00382	.0148	-.0315
	(.0106)	(.0389)	(.0132)	(.00815)	(.0199)	(.0296)
Adjusted R^2	.0379	.00104	.0105	.0278	.00239	.000954
Observations	14,848,153	14,848,153	14,848,153	14,848,153	14,848,153	14,848,153
B: Documentary 2						
DRD	-.000462	-.000094	-.000389	-.000902	-.000303	-.000187
	(.000526)	(.00015)	(.000417)	(.000641)	(.000319)	(.000181)
$\overline{Y}_{\text{Pre}}$	.0499	.00401	.0317	.0795	.0188	.006
DRD / $\overline{Y}_{\text{Pre}}$	-.00927	-.0235	-.0123	-.0114	-.0161	-.0312
	(.0105)	(.0375)	(.0131)	(.00807)	(.017)	(.0302)
Adjusted R^2	.0384	.00114	.0111	.0293	.00292	.00106
Observations	15,061,063	15,061,063	15,061,063	15,061,063	15,061,063	15,061,063

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Eicker-Huber-White standard errors in parentheses. Practice fixed effects and age fixed effects are included in all specifications. Both documentary samples are based on a 3 month window around the respective documentary month. We use the approach of Calonico et al. (2014) to calculate optimal bandwidths. In this setting, time (months) is our running variable. All specifications are based on a polynomial of order one in time. Source: CPRD Aurum.

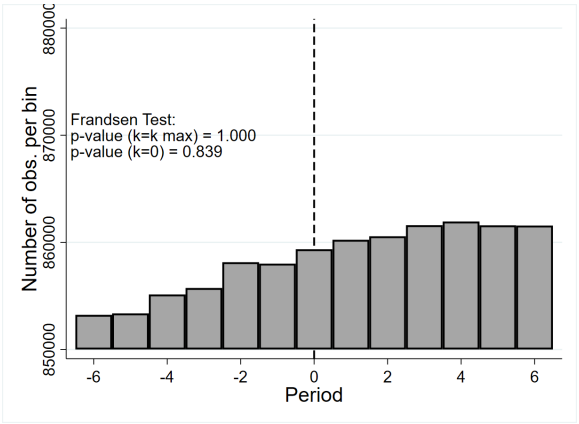
C.4 Density Tests

Figure C2: Density Tests for Both Documentaries

First Documentary

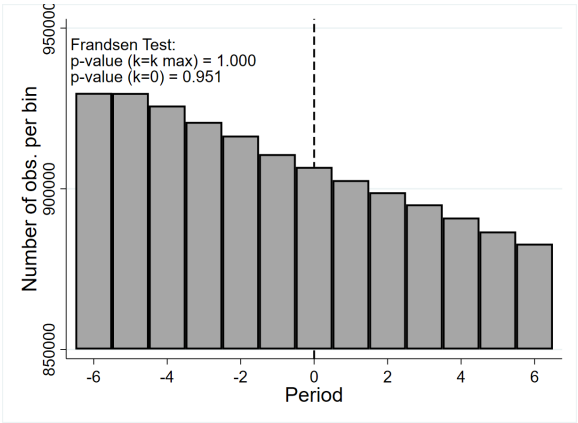


(a) Untreated Cohort

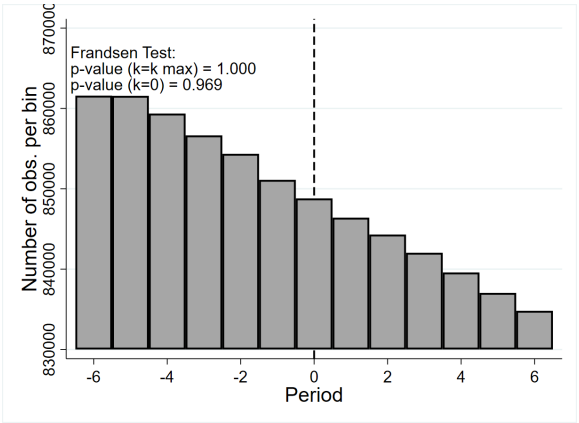


(b) Treated Cohort

Second Documentary



(c) Untreated Cohort



(d) Treated Cohort

D Identification of the Intensive-Margin Estimand

The intensive-margin estimand corresponds to the DRD contrast in T_{im} estimated within the subsample of individual-months for which $E_{im} = 1$. Since E_{im} responds to the documentaries (Table 2), this conditioning introduces a potential, bad-control-induced composition problem (Angrist and Pischke, 2009). Just before the cutoff, the $\{E_{im} = 1\}$ subsample contains only women who would have consulted regardless of the broadcast. Just after, it additionally contains documentary-induced new entrants, who may have different conditional prescribing rates. An estimator that does not account for this shift will confound the treatment effect on T_{im} with the compositional change in who reaches the consulting room.

D.1 How our DRD Design Addresses the Composition Problem

Identification of the intensive-margin estimand within the $\{E_{im} = 1\}$ subsample relies on two conditions, both of which extend naturally from the core DRD assumptions in Section 4.

In a neighborhood of $Z_m = 0$, women in the $\{E_{im} = 1\}$ subsample can be partitioned into two latent types according to their consultation potential outcomes.[8] Always-consulters would enter menopause-relevant care regardless of documentary exposure: $E_{im}(0) = E_{im}(1) = 1$. Documentary-induced consulters enter care only as a result of the broadcast: $E_{im}(0) = 0$, $E_{im}(1) = 1$. Given that the documentaries raised the salience and perceived legitimacy of menopause-related care, there is no credible mechanism through which they would reduce consultation among women who would otherwise have sought menopause-relevant care; the partition is exhaustive in the neighborhood of the cutoff. In the months before the broadcast, the $\{E_{im} = 1\}$ subsample therefore contains only always-consulters. In the broadcast month and after, it additionally contains documentary-induced consulters, who may have different conditional prescribing rates. The group-specific discontinuity in T_{im} conflates a treatment effect on T_{im} for always-consulters with a composition effect from these new entrants. The DRD resolves this by differencing across age cohorts. Under the conditions below, the composition effect cancels, and the estimator recovers the treatment effect on T_{im} for always-consulters.

Assumption D.1: Common untreated discontinuity in T_{im} for always-consulters across groups. We define the untreated discontinuity in T_{im} at $Z_m = 0$ for always-consulters

[8] We borrow this typology from Imbens and Angrist (1994) as an analytical device to characterize the composition of the $\{E_{im} = 1\}$ subsample around the cutoff. The identification strategy here is distinct: there is no instrument and no exclusion restriction, and identification is achieved through the DRD across age cohorts rather than by IV.

in group d as $\delta^{(0)}_{d,\,\mathrm{AC}}$. The required restriction is

$$\delta^{(0)}_{1,\,\mathrm{AC}} = \delta^{(0)}_{0,\,\mathrm{AC}}.$$

This is Assumption 2 of Section 4 applied to the always-consulter subpopulation. Direct support comes from Table D1, which shows no differential discontinuity in predetermined characteristics within the $\{E_{im} = 1\}$ subsample, as we discuss below.

Assumption D.2: Common conditional prescribing rates for documentary-induced consulters across groups. Documentary-induced new entrants in the treatment and control cohorts have the same conditional prescribing rate in a neighborhood of the cutoff:

$$E[T_{im}(1) \mid \mathrm{DC},\, D_i = 1,\, Z_m \approx 0] = E[T_{im}(1) \mid \mathrm{DC},\, D_i = 0,\, Z_m \approx 0]\,.$$

This condition cannot be tested directly, but its plausibility follows from the institutional setting and is supported by the pattern of our core results, as we discuss below.

Assumptions D.1 and D.2 are sufficient for the composition effect to cancel in the DRD when the share of documentary-induced consulters entering the $\{E_{im} = 1\}$ subsample at the cutoff is equal across groups. Since the documentaries differentially shift entry for the treatment group, this share condition will not hold exactly. Cancellation then additionally requires that conditional prescribing rates for documentary-induced consulters are approximately equal to those of always-consulters within each group, so that the unequal shares are applied to a negligible prescribing gap. We provide evidence for this in Section D.2.

D.2 Plausibility and Supporting Evidence

Table D1 presents the analogue of Table C1 within the $\{E_{im} = 1\}$ subsample – DRD estimates for predetermined patient and practice characteristics conditional on entry. Across both documentaries, patient and practice IMD deciles show no differential discontinuity, which is the dimension most relevant for interpreting the intensive-margin estimates given the socioeconomic gradient we document in Section 5.4. Age is broadly balanced, though for Documentary 2 the DRD estimate is negative and statistically significant, indicating that documentary-induced new entrants in the treatment group are on average around four months younger than their control-group counterparts at the cutoff. This differential is small relative to the ten-year span of each cohort and to the baseline mean (a reduction of 0.7%). It therefore does not generate a material

composition effect on T_{im}. The absence of IMD differentials and the negligible magnitude of the age differential support Assumption D.1.

Table D1: DRD Estimates – Patient and Practice Characteristics Conditional on Entry=1

	(1)	(2)	(3)	(4)	(5)	(6)
	Documentary 1			**Documentary 2**		
	Age	Patient IMD Decile	Practice IMD Decile	Age	Patient IMD Decile	Practice IMD Decile
DRD	.128	-.146	-.00194	-.356***	.0719	.0342
	(.169)	(.154)	(.196)	(.117)	(.117)	(.149)
$\overline{Y}_{\text{Pre}}$	49.8	4.77	5.37	49.9	4.58	5.22
DRD / $\overline{Y}_{\text{Pre}}$	.00256	-.0306	-.00036	-.00714***	.0157	.00655
	(.0034)	(.0322)	(.0365)	(.00236)	(.0256)	(.0285)
Adjusted R^2	.468	.483	.00221	.449	.484	.00179
Observations	79,223	67,189	79,250	119,639	99,760	119,660

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Eicker-Huber-White standard errors in parentheses. Practice fixed effects and age fixed effects are included in Patient IMD specifications. For Practice IMD Decile regressions, we remove the practice FEs. For Age regressions, we remove the age FEs. Both documentary samples are based on a 3 month window around the respective documentary month. We use the approach of Calonico et al. (2014) to calculate optimal bandwidths. In this setting, time (months) is our running variable. All specifications are based on a polynomial of order one in time. Source: CPRD Aurum.

Assumption D.2 requires that once a documentary-induced new entrant reaches a menopause-relevant consultation, the probability of being prescribed HRT does not differ across the two age cohorts at the cutoff. This is supported by the institutional setting. Prescribing within consultations is governed by NICE guidelines that apply uniformly across both cohorts and that were stable throughout the study period. There is no institutional mechanism through which the documentaries would differentially alter within-consultation prescribing rates for new entrants in one cohort relative to the other. Moreover, the same institutional features imply that documentary-induced consulters and always-consulters face the same clinical guidelines and prescribing norms once in the consulting room, limiting the scope for within-group differences in conditional prescribing rates between the two latent types.

Three features of the results support both the cross-group restriction of Assumption D.2 and the within-group plausibility argument above. First, baseline conditional prescribing rates are already high – 66.4 per cent and 74.9 per cent in the pre-documentary periods – limiting the scope for any composition effect to materially alter the conditional mean. Second, the spillover analysis in Section 5.3 finds no documentary-induced change in any non-HRT prescription category within menopause-relevant consultations (Table 3), indicating that prescribing decisions within the clinical encounter are unmoved across the full treatment bundle. Third, the T_{im} estimates

are small relative to baseline means and precisely estimated, consistent with the absence of both a treatment effect for always-consulters and any residual composition effect that Assumption D.2 does not cancel.