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Piling Pills? Forward-Looking Behavior and Stockpiling of Prescription Drugs

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Abstract

This paper provides evidence of forward-looking behavior in the demand for prescription drugs, while relying on registry-based, individual-level information about the universe of Danish prescription drug purchases from 1995–2014. We exploit a universal shift in policy in early 2000 from a flat-rate to a non-linear insurance plan for prescription drugs that incentivizes stockpiling at the end of the coverage year. We extend the original framework of Keeler et al. (1977) and discuss how the institutional features of most health insurance contracts, at least theoretically, incentivize intertemporal substitution in purchases across coverage years. We describe how consumers react to the introduction of the non-linear plan by increasing spending by 80% immediately before the implementation of the new regime. Next, our main analysis takes advantage of the policy experiment to formally analyze behavior immediately prior to the end-of-year reset in the non-linear plan using a difference-in-difference strategy. We provide evidence that consumers react to this reset by stockpiling toward the end of the coverage year: consumers buy what amounts to an additional 20%. We detect heterogeneity in the size of the response by individual-level characteristics, proxies for health status, and drug type. We find no evidence of any immediate adverse health utilization effects associated with the stockpiling. We round off the paper with an analysis of the importance of stockpiling for estimates of price sensitivity. We find that ignoring intertemporal substitution across coverage years inflates price sensitivity estimates by a non-negligible amount.

Keywords: prescription drugs; non-linear pricing; intertemporal shifting

JEL: I11, I18, D12

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I. Introduction

This paper provides empirical evidence of forward-looking behavior in the demand for outpatient prescription drugs. In particular, we see that consumers shift the timing of their purchases and stockpile immediately before a known increase in the spot price. For policymakers to improve on existing health insurance contracts, studies with explicit attention to the responses and reactions to these dynamic features of most health insurance contracts are needed (see Einav et al., 2015). If healthcare consumers can forecast and stockpile or postpone purchases, then existing static or within-period (spot) price elasticity estimates will be upward-biased. We demonstrate this empirically. Convincing price-sensitivity estimates are especially important because health care costs continue to rise: in recent decades, health spending in OECD countries has grown more rapidly than in the rest of the economy, absorbing an increasing share of the gross domestic product. Pharmaceutical expenditure accounts for one fifth (19%) of all health expenditures; has a growth rate of more than twice that of total health expenditures; and is foreseen to increase even further in the future, putting severe pressure on health care budgets (OECD, 2009, 2011).

Our analysis exploits a major policy experiment in Denmark. Prior to March 2000, prescription drugs were subsidized using a fixed coinsurance plan depending only on the therapeutic type of the drugs. On March 1, 2000, the government introduced a non-linear plan whereby the coinsurance rate decreases as total expenditures on drugs accumulate over a coverage year. This type of pricing contract and the price variation it generates is, in fact, very common in many countries due to the design of public and private health insurance plans. The non-linearity of the pricing scheme means that purchases today affect prices faced by the healthcare consumer tomorrow. Moreover, and for our purposes these are the key distinguishing features of the Danish plan design: 1) a consumer's account is reset exactly one year after the initial purchase and 2) after reset, a subsequent coverage year will start with the next purchase (i.e., not the next day). The former characteristic will (sometimes) generate a discrete spike in the spot price of drugs between the last day of the current coverage year and the first day of the next, while the latter implies that the timing of the initiation of a subsequent coverage year is endogenous: it is at least to some extent within the individual's control. In practice, unlike other types of healthcare goods, the storability of most prescription drugs enables the consumer to detach the timing of purchase from the timing of consumption. We extend the original framework of Keeler et al. (1977) and discuss how the institutional features of most health insurance contracts, at least theoretically, incentivize intertemporal substitution in purchases across coverage years.

The fact that healthcare consumers can effectively stockpile prescription drugs for future consumption when prices are low (relevant in the Danish case outlined below) or postpone purchases and consumption when prices are high (as in the American donut hole of Medicare Part D) has, to the best of our knowledge, received limited empirical (and theoretical) attention—and first only very recently.

Our paper relates to several recent strands of literature within this particular area. One group of papers addresses the reactions to insurance contract reforms, be they publicly or privately provided. Skipper (2012), for example, presents early evidence of how the introduction of the current non-linear Danish coverage plan for prescription drugs induced stockpiling among diabetics. Similarly, Alpert (2016) studies the anticipatory effects on drug consumption of the announcement of Medicare Part D, which lowered future drug costs, and Brot-Goldberg et al. (forthcoming) analyze a shift from free health care to a non-linear insurance contract in a large private firm. All three document major pre-reform responses. Another approach is to consider the anticipatory behavior within a coverage period: Aron-Dine, Einav, Finkelstein, and Cullen (2015) use data on employer-provided health insurance and Medicare Part D. They exploit how individuals employed at different points in time in the calendar year will face similar spot prices but different expected-end-of-year prices to show that individuals do take the latter into account when making purchasing decisions. Einav, Finkelstein, and Schrimpf (2015) document the bunching of annual drug spending as individuals enter the donut hole in Medicare Part D, where insurance becomes discontinuously much less generous. Einav, Finkelstein, and Schrimpf (2015) acknowledge and incorporate in their analysis that intertemporal substitution between coverage years, though incentives are possibly much less salient, may affect their main estimates, and a few recent studies directly investigate such strategic behavior. Cabral (2017), for example, uses firm-level data to document how the individuals who were likely to exceed their maximum dental treatment benefits postponed treatment to early January. Lin and Sacks (2016) return to the famous RAND health insurance experiment[1] and produce evidence of economically significant intertemporal substitution in healthcare demand for individuals randomized into high-deductible plans.[2]

[1] See Aron-Dine et al. (2013) for a long-term evaluation of the RAND health insurance experiment.

[2] Our paper is also naturally related to a broader literature about consumer responses to non-linear pricing (see Chetty et al. (2011) about taxes and Ito (2014) about demand for electricity) and to work on links between sales and consumer inventory behavior (see e.g. Hendel and Nevo (2006)): the discrete spike in the prescription drug spot price on the first day of a new coverage year could be perceived as an announced end of a sale. The stockpiling of drugs documented in this paper is also in some sense similar to the retiming of income for tax-minimizing purposes (see e.g. Stiglitz, 1985; le Maire and Schjerning, 2013; Kreiner et al., 2016).

Contrary to the existing literature that has relied on single-firm data or data available (and policy variation relevant) for the elderly population only, our empirical analysis is based on population-wide registry-based Danish data. These include information about all prescription drug purchases made by adult residents in Denmark as well as their health outcomes and socio-economic background variables during the period 1995–2014. First, this allows us to address key neglected issues such as external validity and core heterogeneity across subgroups of the population. Second, with these data at hand, we are able to provide the first analysis linking consumers' strategic responses to policies to subsequent health outcomes; a critical input into any meaningful welfare analysis. Third, the long panel facilitates the analysis of learning. As discussed in DellaVigna (2009), repeated experience is important for individuals' ability to perform backward induction; hence, the existing short panels employed are less likely to be informative in this regard. Finally, links between individuals and general practitioners enable us to delve into the role of the prescribing physician in supporting strategic behavior.

We start by describing how consumers react to the introduction of the non-linear plan by purchasing substantially higher amounts immediately before the implementation of the new regime: even when faced with a high pre-reform actuarial value (.67), in February 2000, the month immediately prior to the reform, Danes spent more than 80% more than in February 1999. Importantly, we find no evidence of any supply responses from pharmacies or pharmaceutical companies. Next, we characterize behavior within the non-linear plan in greater detail.[3] To analyze reactions to the end-of-year reset formally, we implement a difference-in-difference strategy, first comparing one individual's purchase patterns toward the end of a coverage year with the same individual's purchase patterns slightly earlier in the coverage year. Our strategy then compares behavior before and after the introduction of the non-linear plan. We find that consumers react to this future spot price increase by purchasing 20% more toward the end of the coverage year. We detect heterogeneity in the size of the response by individual-level characteristics such as age, by proxies for health status, and by drug type. Conversely, we find some evidence that prior knowledge about the plan elucidates the relatively subtle incentives and leads to increases in the tendency to stockpile. That is, we find evidence of increasing amounts or incidents of stockpiling as consumers gain experience with the new policy regime. Reassuringly, we find no evidence of adverse health effects, which is important for understanding the welfare

[3] The setup with individually timed coverage year leaves very little scope for pharmacies and pharmaceutical companies to behave strategically around resets in the after-reform period.

consequences associated with the purchasing behavior of the marked increase in the immediate availability of prescription drugs.

To learn more about the nature of the observed behavior, we explore the monetary gains associated with the retiming of purchases. We find that these are actually relatively small for most consumers and that only part of the population stands something to gain. Moreover, stockpiling has become less attractive over time. Given that we see a considerable share of consumers retime their purchases, we conclude that individuals are highly sensitive to resetting the coverage year. We round off the paper with an analysis of the importance of stockpiling for price-sensitivity estimates with inspiration from the analysis of Brot-Goldberg et al. (forthcoming). We find that ignoring intertemporal substitution across coverage years inflates price-sensitivity estimates by a non-negligible amount.

The remainder of the paper is structured as follows: Section II outlines the relevant institutional background and presents a simple conceptual framework. Section III details our data and documents the initial reaction to the policy reform. Section IV quantifies behavior within the non-linear plan and Section V presents robustness analyses. Section VI investigates the effects of stockpiling on health care utilization and health outcomes. Section VII quantifies the gains associated with the observed behavior and Section VIII investigates the consequences for within-coverage year price estimates. Finally, Section IX concludes.

II. Institutional background and a simple conceptual framework

II.A. Institutional details: from a flat-rate to a needs-based coverage plan for prescription drugs

This section sets the scene by briefly describing the Danish outpatient prescription drug reimbursement plans before and after the major reform on March 1, 2000. We then compare the new plan to a stylized theoretical model of demand for prescription drugs and relate this to the current research.

Health care is generally tax-financed and free of charge in Denmark, prescription drugs an important exception. Only licensed physicians can write prescriptions, but consulting the physician and the prescription itself are free of charge. Physicians have no financial incentive to prescribe expensive medication or certain brands or drug groups. In fact, there is no separate charge for writing a prescription at all. Except for heavily addictive substances (e.g., opioids (pain) and benzodiazepines (anxiety)), there are no restrictions on the amounts of drugs that can be prescribed;[4] that is, there are no laws against stockpiling in Denmark, neither pertaining to the patient nor the physician.

The Danish coverage plan for prescription drugs underwent a major change in March 2000, from a system with a fixed coinsurance (own payment) rate, depending on drug type, to one where the coinsurance rate became dependent on total expenditures in a non-linear fashion. The work leading up to the reform was initiated with the establishment in early 1997 of a government-appointed expert committee (*Medicinudvalget*). Both this work as well as the subsequent law received regular—and considerable—attention in the press in the years leading up to the policy change. The details of the needs-based system were first announced in November 1998. The law was passed on December 23, 1998 (see Simonsen et al., 2016).

Prior to the reform, a low coinsurance rate (25%) applied to drugs targeting well-defined and what were considered to be life-threatening illnesses (e.g., high blood pressure, cardiovascular disease). A higher rate (50%) applied to all other approved prescription drugs, the most common being antibiotics and (larger packages of) analgesics (painkillers). Insulin, a special case, was offered for free.[5]

Table 1 documents the pre-reform spending patterns across the three coinsurance rates based on purchases made in the pre-reform year of 1999. The majority of prescriptions lie in the low, 25% coinsurance rate group; the concentration is even higher in terms of defined daily doses (henceforth *DDD*) and total expenditures. This implies that prescriptions in the high coinsurance rate of 50% were typically cheaper and covered a shorter period.

[4] The authorities monitor GPs' total prescriptions of these drugs (not individual prescriptions). Authorities react if prescription numbers are "unusually high."

[5] See Appendix A for lists of top-10 types of pharmaceuticals within each coinsurance rate based on *Rx* counts in the year prior to the reform, 1999.

TABLE 1

PRE-REFORM (1999) DISTRIBUTION ACROSS COINSURANCE RATES

Coinsurance rate	*Rx*	*DDD*	Total Expenditures
50%	44%	32%	29%
25%	55%	66%	68%
0%	1%	1%	3%

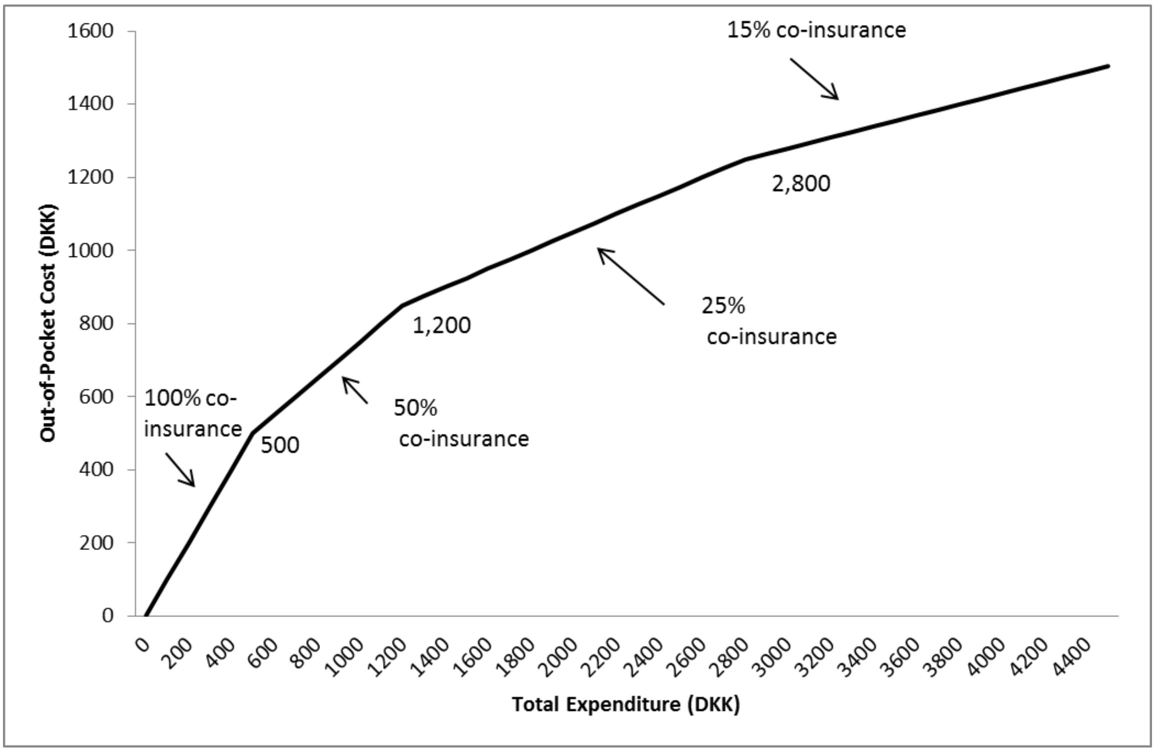
Notes: *Rx* is prescriptions, *DDD* is defined daily dose in terms of volume (cf. the World Health Organization), and *Total Expenditures* includes both government and consumer outlays. Own calculations based on total prescription drug spending among adults in Denmark in 1999, the pre-reform calendar year.

The post-reform, universally supplied contract is illustrated in Figure 1 below:[6] after an initial deductible of DKK 500 (€70), consumers pay 50% of additional expenditures out of pocket until reaching the second threshold at DKK 1,200 (€160). Here, the coinsurance rate drops to 25% and further to 15% after DKK 2,800 (€370). A full stop-loss after DKK 18,500 (€2,470) effectively caps out-of-pocket costs at DKK 3,600 (€480). On average, less than 2% of consumers hit the stop-loss limit during their coverage year; see Figure 2 below. The coverage is provided annually on an individual basis, like auto and home insurance, meaning that total expenditures are reset to zero 365 days after the first purchase. A new coverage year first begins the next time a prescription drug is purchased. Below, we will discuss the political motivation behind the schedule as well as the implications for purchasing behavior.

[6] The coinsurance rates and structure have remained the same since 2000, but the real value of the deductible has increased by 40%, whereas subsequent thresholds for the coinsurance tiers and the catastrophic limit have dropped as much as 30% over the years, effectively making the system slightly more progressive today than at inception (see Appendix A, Figures A1–A2).

FIGURE 1

THE DANISH POST-REFORM COVERAGE PLAN FOR PRESCRIPTION DRUGS



Notes: The out-of-pocket costs are graphed as a function of total expenditures with the three coinsurance thresholds as of March 2000. The coverage is provided annually on an individual basis. In addition (and not depicted), there is a full stop-loss after DKK 18,500 (€480).

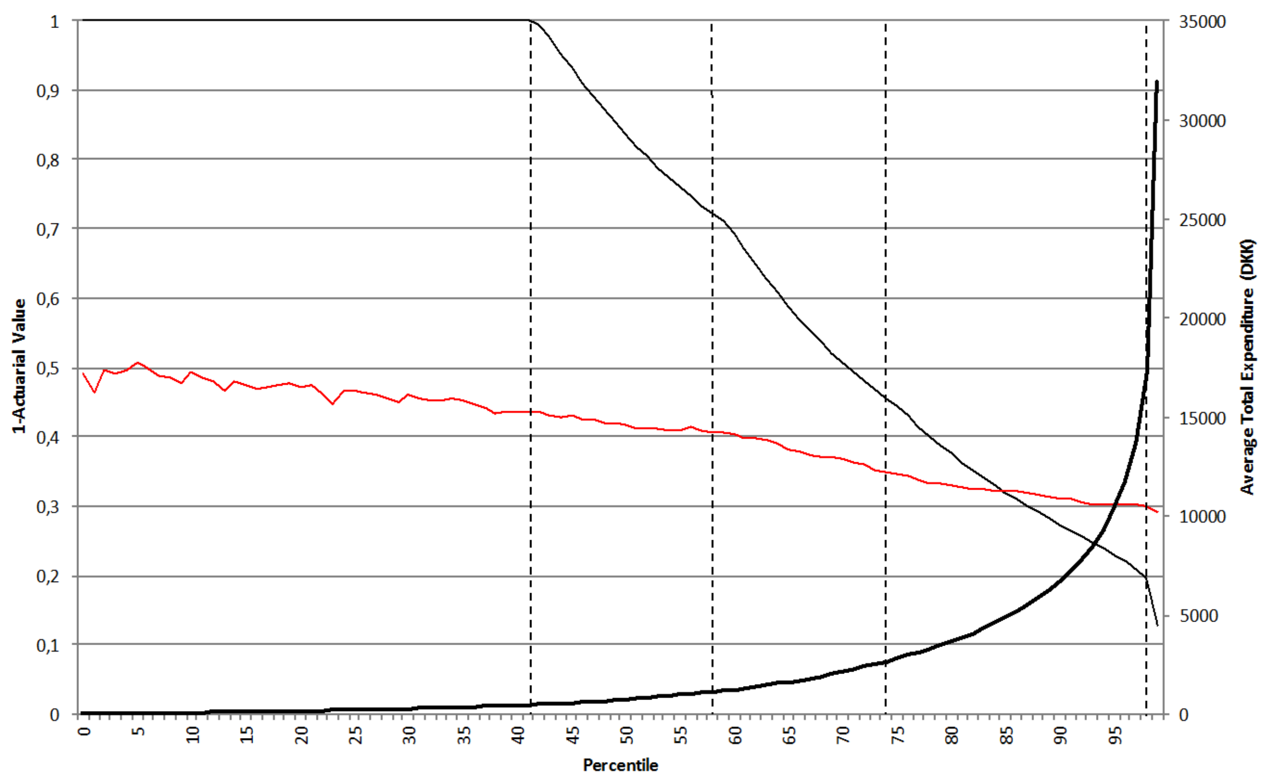
Other means-tested subsidies existed both prior to and after the reform but neither of these interacts with the non-linear plan. Around 8% of the individuals who purchased drugs in the reform-year of 2000 received additional public coverage. In addition, one company, *danmark*, provides supplemental insurance for prescription drugs. They offer two insurance plans: Type I membership (18% of the adult population in 2000) that covers half of the remaining out-of-pocket costs for prescription drugs, and Type II membership (11% of the adult population in 2000) that covers all remaining out-of-pocket expenditures. None of danmark’s policies change with the yearly consumption of prescription drugs. Furthermore, non-members cannot enroll if they have purchased any prescription drugs during the last 12 months, nor can individuals over aged 60 without previous insurance; hence, there is very little opportunity for supplemental insurance to respond to short-term health shocks.

Figure 2 compares the average out-of-pocket shares of total expenditures (or 1 minus the actuarial value) of the two regimes across the pre-reform distribution of yearly prescription drug spending for 1999. In so doing, we ignore any behavioral responses to the dramatic shifts in actuarial value for most consumers. Firstly, consumers might already react to the future introduction of the new plan in 1999. Secondly, purchasing behavior may simply be different *within* the new regime. We will show below that the former channel is negligible.[7] We observe a downward-sloping trend across the distribution of total expenditures prior to the reform, the least-consuming individuals paying on average 50% of their total expenditures and the most heavily consuming individuals paying about 30% of the total expenditures out of pocket. This is driven by the types of drugs consumed; the highest-spending consumers are more likely to be diabetic and/or to buy drugs targeting well-defined, life-threatening illnesses with the lower coinsurance rate of 25%. The distribution of average coinsurance would change dramatically with the reform; imposing the post-reform regime on the 1999-spending distribution, for example, more than 40% of consumers would have spending levels under the deductible and receive no coverage at all. In fact, the vast majority of consumers (85%) faced a lower imputed actuarial value after the introduction of the needs-based plan. For the government, on the other hand, the shift from a flat-rate to a needs-based plan was for all practical and intended purposes budget-neutral; the actuarial value was 0.67 pre-reform and (expected) 0.65 post-reform.

[7] Consumers did only react in the first months of 2000, immediately prior to the reform.

FIGURE 2

PRE-REFORM DISTRIBUTION OF PRESCRIPTION DRUG SPENDING AND CELL-AVERAGE PRE- AND IMPLIED POST-REFORM ACTUARIAL VALUES



Notes: Average total expenditures on percentile level (thick black line, right axis) and pre- (gray—or red if read online, left axis) and synthetic post-reform (thin black line, left axis) average share of total expenditures paid out of pocket. The synthetic post-reform schedule ignores consumer price sensitivity. The four dotted vertical lines separate the distribution into the five post-reform tiers using the coinsurance thresholds as of March 2000 (see Table 1). Own calculations based on total prescription drug spending among adults in Denmark, 1999.

In the government white paper behind the reform (Sundhedsministeriet, 1998) the individual specific coverage year was favored over a fixed calendar year due to stockpiling-related issues: whereas a system with individual coverage years would smooth out potential end-of-period stockpiling over the months of the year, a calendar-based system with a re-zeroing of accounts every January might lead to runs on pharmacies in December.[8] As demonstrated in the next section, the individual-based

[8] The report also states that “[a]ll things considered the amount stockpiled will most likely be smaller if the time where the individual patient faces a low coinsurance rate is specific to that individual.” This point is never elaborated on.

coverage year with endogenous initiation created an additional but subtle incentive to stockpile; one that was neglected in the white paper and discussions in the media when the legislation was implemented. Since a new coverage period first starts on the date of the first purchase after the expiration of the previous coverage year, stockpiling mechanically postpones the onset of the next coverage year and therefore systematically leads to fewer initiated coverage years over time, thereby generating an additional incentive beyond the apparent effect of buying when coinsurance rates are low.

II.B Conceptual framework

The theoretical model that captures all of the dynamic, within-coverage year features of the current Danish prescription drug reimbursement plan is outlined and thoroughly discussed in Keeler et al. (1977). We briefly present it here in a modified version adapted to a stylized case: at time *t*, consumers can exercise their preferences between a composite good, c_t, and prescription drugs, Rx_t, where the latter is priced at p_{Rx}. We consider the simplest of cases: one change in coinsurance rate from 100% to *C* after deductible *D* is exceeded and no catastrophic limit. Hence, consumers pay p_{Rx} if total consumption is under *D* but only Cp_{Rx} on the part of consumption exceeding *D*. Within-coverage-period total expenditures ($\sum p_{Rx}$) are denoted by *TE*. The actuarial value—the government's share of total expenditures—of the plan in a given coverage period is then defined as $(1 - C) \times \left(1 - \frac{D}{TE}\right) \times \mathbb{I}_{(TE \geq D)}$. The utility function, $U(c_t, H_t)$ is defined over other goods and (perceived) health, H_t. Use of prescription drugs is assumed to alleviate illness and thus increase health.

First, consider the dynamics of consumption *within* a given coverage year, as in Keeler et al. (1977). With uncertainty about future needs for prescription drugs, purchases under *D* will add to the total expenditures and, hence, bring the consumer closer to *D*. For consumption below *D*, there are therefore two effects: the alleviation of today's ailment as well as reducing the expected costs of future drug consumption. The more likely a future need for prescription drugs (within the coverage year) will bring the consumer above *D*, the cheaper today's consumption. The current *spot* price at the time of purchase should therefore only be relevant to a myopic consumer. A rational, forward-looking consumer should form expectations about future (within-period) needs and respond to the expected end-of-year price. Due to the nonlinear plan induced by (*D*, *C*), the purchasing decision within a coverage period therefore depends on this *expected marginal price* (not the current spot price). In other words, consumers facing a decision to buy a prescription drug at time t, Rx_t, should form expectations about both future random shocks to their health capital, H_τ, from now and until the end of the coverage period (where the cumulated expenditure account is re-zeroed) and the expected cumulated expenditures of treating or alleviating the consequences of these shocks.

If stockpiling is an option, however, consumers are incentivized to look beyond the current coverage period when making purchasing decisions. To illustrate how the structure of the plan affects purchase timing, consider the following simple example: assume that drugs are storable (the quality or potency of the drugs does not decay over the relevant time horizon) and that there are no storage costs. Consumers form expectations about future needs, and prescribing physicians do not impose restrictions on stockpiling. Such consumers face a considerable utility loss from not taking their medicine, allowing us to focus on the timing of purchases rather than consumption decisions *per se*. Finally, consumers will not expect any cheaper (e.g., because of patent expiration) or better future generations of the drugs to appear during the stockpiling period. This reduces the consumers' problem to an exercise of minimizing their total expected out-of-pocket costs across coverage years.

Nearing the end of their coverage period, consumers are able to buy today and consume the drugs in the future. As stockpiling today lowers the expected future purchasing, it also lowers the expected future cumulated expenditures, therefore reducing the likelihood of consumers reaching the deductible, D, within the *next* coverage period. Hence, stockpiling at the end of one coverage period increases the expected marginal price in the subsequent coverage period and, consequently, lowers the *effective* marginal benefit of stockpiling. Thus, just as consumers would be mistaken to act only on the spot prices within a coverage period, myopic consumers reacting to the change in the spot prices from one day to the next because of the expiration of the coverage year would also greatly overstate the benefit of stockpiling. What should be compared and contrasted (when contemplating the opportunity to stockpile) instead is the current out-of-pocket cost with the expected end-of-year marginal price in the subsequent coverage periods,[9] *ceteris paribus*. With a deductible D and a single change in the coinsurance rate from 100% to C, only consumers with current-period spending levels above D but expected next-period cumulated spending levels under the deductible D would see a change in the *effective* expected marginal price by stockpiling: This would be lowered by $(1 - C) \times$

[9] Just as shifting income from one calendar year to the next for tax planning purposes only makes sense if one expects to face a lower marginal tax rate in the subsequent year.

p_{Rx}. Consumers currently above (under) D and with a future coverage period consumption level expected above and beyond (still under) D would not be changing the effective expected marginal price by stockpiling: the out-of-pocket price on the marginal prescription will be Cp_{Rx} (p_{Rx}) in both the current and subsequent coverage periods. Finally, consumers under D but expecting to be above D at the end of the next coverage period would be ill-advised to stockpile: they would be buying the marginal prescription drug today at p_{Rx} instead of Cp_{Rx} the following year. Hence, in a more general setup with multiple and declining coinsurance rates, the gain from end-of-coverage-period stockpiling becomes a nonlinear function increasing in the current period consumption level, decreasing in the expected future consumption level, and increasing in the shelf-price of the stockpiled drugs.

The discussion above would suffice if the coverage year were fixed in the sense that a new coverage period would commence immediately after the expiration of the old, as in a standard calendar-based system. All that mattered for the incentive to stockpile would then be the effect on the price, discussed above, running through the potential changes in the effective expected marginal price. In the Danish post-reform context with coverage years that are first initiated once a purchase is actually made, however, stockpiling mechanically postpones the expected onset of a new coverage period. That is, unless consumers are hit by an *un*expected adverse health shock requiring treatment in the near future, they can wait and first initiate a new coverage period once their stock of prescription drugs is depleted. In this case, therefore, end-of-coverage-period stockpiling has no consequences for expected future purchasing need in the *following* coverage period and, hence, no effect on expected end-of-year prices in subsequent periods. While there will be an effect on price, the mechanism will be different from the calendar-based system. For consumers close to but under the deductible, stockpiling *lowers* the current marginal price. Essentially, for such consumers nearing the end of the coverage year, the current plan dominates the future plan because the marginal price (spot price) is strictly lower than the expected out-of-pocket fraction inherent in any future coverage period (or one minus the actuarial value of such a future coverage period). Marginal purchases today can be made at Cp_{Rx}, whereas no matter the future needs and corresponding expected total expenditures, after reset some purchases will still have to be made under the deductible, where consumers face the full price, p_{Rx}. The actuarial value—the percentage of total average costs covered by the government-supplied insurance—of any remaining purchases made at the end of the present coverage year will be higher than the actuarial value of future coverage years. Stockpiling gives the consumers close to or above D benefit from staying on the current plan, which strictly dominates the future plan.

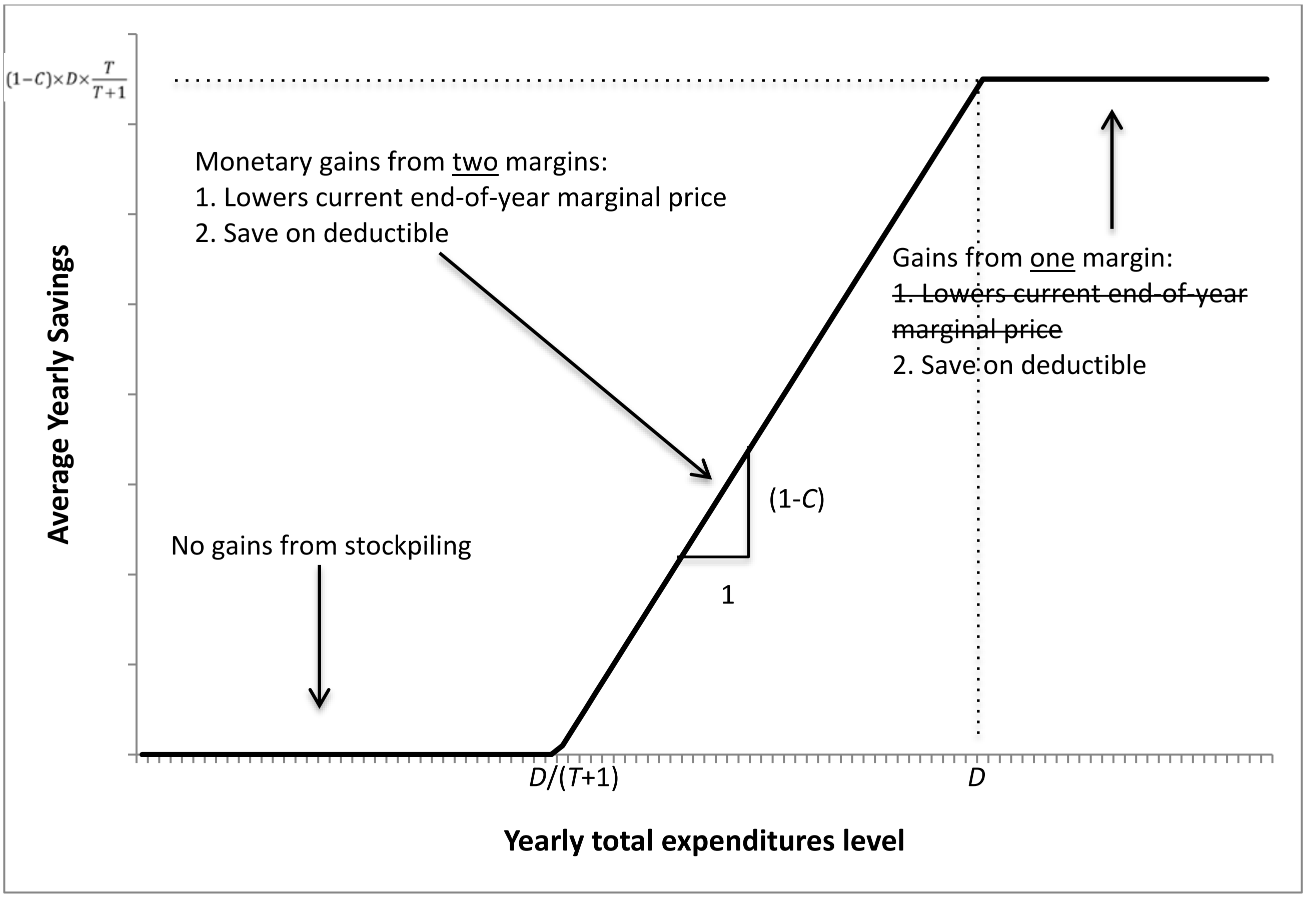
Part of this benefit is an income effect for everyone (except those whose purchases never exceed the deductible, even with stockpiling) generated because of the endogenous initiation of coverage periods inherent in the Danish coverage plan. This effect comes from the fact that, over a longer time horizon, stockpiling consumers reduce the number of initiated coverage years and save on the number of times they pay the full price p_{Rx} on the first drugs consumed. In the Danish context, both the effect on the price of stockpiled products and the income effect favor stockpiling, as they both increase the actuarial value of the plan.

To illustrate, imagine consumers in a world that is stationary both on the supply side (no new drugs expected to enter the market, p_{Rx} not expected to change) and demand side (stable health and income), and assume that the physician can be convinced to prescribe a year's supply of drugs at the end of a coverage year. Consumers with yearly drug expenditure needs above D will not face a different marginal price whether stockpiling or not: in both cases, the marginal price is Cp_{Rx}, as the consumers are above D irrespective of their choice to stockpile. If they decide to stockpile, however, they do not face the full price of the first D spent on the drugs needed for the second year. Hence, stockpiling produces savings equal to $(1 - C) \times D$ on the inframarginal products even though the effective marginal price remains unchanged (these savings obviously come from making a purchase today and should be compared to the properly discounted outlays in the future, slightly reducing the actual benefits). Low-demand consumers with a yearly drug expenditure level below $D/2$ are the only consumer type not experiencing this economic benefit when given the option to stockpile a year's supply: stockpiling so many pills at the end of a coverage year only ties up liquidity in pills (and forwards the costs) without changing the price on any of the purchased drugs: every drug purchased is bought at the shelf price p_{Rx}. Finally, for consumers with annual consumption levels between $D/2$ and D, the gains from stockpiling a full year's supply of drugs come from two sources: the gains from having a lower coinsurance rate on the infra-marginal products (the income effect) *plus* the savings from a lower coinsurance rate on the marginal product stockpiled (the effect on price).

Figure 3 illustrates the average yearly gains from stockpiling as functions of D and C in this stationary world, where T is the amount of daily doses stockpiled measured in years (can also be fractions of a year). Allowed to stockpile a full year's supply of drugs ($T = 1$), consumers with yearly spending levels above D save $(1 - C) \times D$ every second year; consumers allowed to stockpile a two-year supply of drugs (T = 2) will save 2(1 – C) × D every three years; whereas consumers allowed to stockpile only a month's worth ($T = 1/12$) save only (1 – C) × D every thirteenth year.

FIGURE 3

AVERAGE YEARLY GAINS FROM STOCKPILING IN A STATIONARY WORLD



Notes: The figure shows monetary gains from stockpiling a fraction of a year's supply of prescription drugs (T) as a function of deductible D and coinsurance rate C in a stationary world with a fixed yearly expenditure level.

The outlined framework includes several clear predictions that can readily be tested empirically: firstly, since we saw above in Figure 2 that the post-reform actuarial value (calculated based on pre-reform expenditure levels) was lower than that of the pre-reform except for those with the very highest spending levels, we expect to see a non-negligible share of forward-looking individuals stockpiling before the reform. With non-zero discounting and in the presence of storage costs, we predict that these additional purchases will take place *immediately* prior to the reform: the way the Danish post-reform system is implemented with individual-specific coverage years results in a situation where fully rational, forward-looking agents should compare the (expected average) spot price within the old regime with the *average* out-of-pocket cost in the first post-reform coverage year when contemplating whether or not to stockpile. Again, stockpiling before the introduction of the reform is a way of maintaining the current plan. For example, consumers in treatment with drugs carrying a pre-reform coinsurance rate of 50% (drugs treating well-defined but not life-threatening illnesses) must expect to spend more than DKK 2,200 (above the 70th percentile) in the first post-reform coverage year for stockpiling not to be beneficial. Even more extreme, consumers considering whether or not to stockpile drugs associated with a 25% pre-reform coinsurance rate have to expect to spend more than DKK 8,350 (above the 92nd percentile) for them not to gain from stockpiling prior to the introduction of the non-linear plan.

Similarly, we expect the re-zeroing of accounts at the end of the coverage year to stimulate stockpiling, resulting in a spike in the purchasing probability toward the end of the coverage year, both compared to within-coverage-year consumption and compared to the period immediately after the re-zeroing. Moreover, for there to be a *realized* income effect of stockpiling, purchases must be concentrated in fewer coverage years with corresponding delays in the initiation of subsequent coverage years.

The benefits of stockpiling depend on future demand. Consumers with high predictable spending should, *ceteris paribus*, have a greater incentive to stockpile than those with low, infrequent needs. Consumers of potent addictive drugs (e.g., opioids) face some restrictions in their ability to stockpile (because of the monitoring of general practitioners (GPs); see above) and should do so less. And finally: since the reform has been in place for more than a decade it is now feasible to address and quantify the salience of the system and study the degree to which consumers over time learn about the system and develop the skills to adequately respond to stockpiling incentives.

III. Data and descriptive statistics: reaction to the introduction of the reform

Our paper uses registry-based Danish data maintained by Statistics Denmark. The data set contains information on the entire adult population of individuals residing in Denmark from 1995 to 2014 (5 years of pre-reform data, 15 years of post-reform data). We know the complete history of prescription drug purchases for each individual, including date, shelf price, amount of government coverage, type of coverage, type of drug, and identity of prescribing physician. Using this information, we construct variables describing the nature of the individual's previous demand. These include the value of previous drug consumption, previous number of drug groups used, and whether or not the individual suffers from a chronic disease based on the nature of previous purchases.[10] The prescription drug purchase data has been augmented with socio-economic information describing demographics, income, and education. Finally, we exploit information about health-care service use and diagnoses associated with hospital interactions.[11]

Table 2 presents descriptive evidence of pre-reform response heterogeneity as measured by the change in total expenditures between February 1999 and February 2000, closely following the presentation of Brot-Goldberg et al. (2017). To start, we observe substantial differences in spending levels in February 1999 across groups; the 25% of the population with the worst predicted health,[12] for example, account for almost 70% of the total spending in February 1999. Similarly, the 8% of the population who purchase at least three drugs targeting chronic diseases account for more than 40% of all spending.

In the absence of the reform, we would expect an increase in consumption in line with the overall trend of 6% for monthly, year-to-year growth rates for January 1995–December 1999 (see Appendix A, Figure A3).[13] Yet the overall trend is dwarfed by the actual change: on average, consumers increase their February consumption by more than 80%. Note that this large response occurs even though 29% of the population has access to supplementary insurance through danmark, removing (for 11% of the population) or substantially limiting (18%) any benefit from stockpiling. Other means-tested subsidies also reduce the gains from stockpiling: among those who received any additional subsidies on their February 2000 purchase, 75% received a subsidy from their municipality on the first purchase made post-reform in 2000. This subsidy covered 72% of the out-of-pocket cost of the first purchase.

The most dramatic responses to the reform are found among individuals in relatively poor predicted health. Those among the 25% with the worst predicted health increase consumption by as much as

[10] In line with Alpert (2016), we classify a drug as targeted toward chronic disease if the median consumer purchases this drug more than twice within a calendar year (see Appendix B).
[11] Individuals who die are excluded from the sample one month before the actual death occurs.
[12] See Appendix C for details.
[13] The std. dev. for the 48 monthly, year-to-year observations is 6%, with a maximum observed monthly year-to-year growth rate of 18% and minimum of -15%.

90%, whereas those in the top 1% increase their spending somewhat less (66% more in February 2000). Interestingly, the top 1% actually have lower monetary incentives to stockpile than the top 25%: their level of consumption is relatively large *but*, as seen in Figure 2, their implied post-reform actuarial value is actually higher than the pre-reform actuarial value. We also see those who are treated with at least one drug associated with chronic disease—who are likely better able to predict future need precisely—stockpile more.

Socio-demographic factors are only weakly associated with the size of the response, although elderly individuals increase their spending more than others. Income not apparently mattering for the response size may be due to different factors pulling in opposite directions. For example, low-income individuals are in worse health, as measured by their level of February spending, and also suffer from more serious (chronic) diseases, as indicated by their actuarial value. We would therefore expect the lowest income quartile to react stronger to the introduction of the reform. But low-income individuals are also less flexible in terms of liquidity to buy in bulk, just as additional subsidies are likely to play a role: among those making a purchase in February 2000, 38% of those in the lowest income quartile receive an additional subsidy from their municipality. In the second income quartile, that fraction is only 8%. A negligible fraction in the top half of the income distribution receive any additional public subsidies (< .3%).[14] This should strengthen their incentives to purchase immediately prior to the reform, but high-income individuals, on the other hand, might also have lower marginal utility of income and, hence, might find stockpiling less worthwhile.

Interestingly, there is hardly any difference in coinsurance rates across purchases in February 1999 and 2000. This implies that consumers did not react to the introduction of the reform primarily by buying drugs with high coinsurance rates.

[14] Conditional on actually receiving an additional subsidy, this covers on average 75–82% of the remaining out-of-pocket cost.

TABLE 2

DESCRIPTIVE STATISTICS AND PRE-REFORM RESPONSE

	Group	1999 Spending	Mean spending Feb 1999 (DKK)	Change in total expen-ditures	Mean actuarial value, Feb 1999	2000
All	N=4,127,847	DKK 1469.98	106.15	0.82	0.66	0.67
	(%)	(%)				
Women	51	58	119.89	0.80	0.66	0.67
Men	49	42	91.79	0.84	0.67	0.68
Income quartile 1999						
]-;DKK 105K]	25	39	164.56	0.82	0.74	0.74
]DKK105K; DKK179K]	25	28	120.49	0.82	0.64	0.65
]DKK179K;DKK256K]	25	17	75.06	0.82	0.61	0.62
]DKK 256K+	25	16	67.63	0.81	0.61	0.62
Age						
< 30	19	6	32.40	0.75	0.58	0.60
30-64	62	53	92.08	0.81	0.64	0.65
> 64	19	41	224.74	0.83	0.72	0.72
Predicted health index quartile						
Q1	25	3	8.73	0.34	0.54	0.54
Q2	25	3	12.03	0.28	0.55	0.55
Q3	25	11	42.64	0.67	0.60	0.61
Q4	24	69	324.06	0.90	0.71	0.72
Top 1%	1	15	1,741.48	0.66	0.80	0.80
#Chronic drugs bought						
0	73	22	31.17	0.19	0.58	0.58
1-2	20	42	237.60	0.92	0.69	0.70
3+	7	35	541.54	1.00	0.75	0.76

Notes: The predicted health index is the predicted consumption of prescription drugs in 1999 (2000) based on 1998 (1999) demographics, consumption, and other medical service use (see Appendix C for details). “Chronic drugs” are drugs that the median consumer buys more than twice during a calendar year (see Appendix B). Chronic drug purchases are measured in the previous calendar year. For all categories, the population is allowed to change age group, quartiles, and chronic status between February 1999 and February 2000. Own calculations based on total prescription drug spending in Denmark in 1999 and February 2000.

Table 3 first demonstrates through Laspeyres’ price and quantity indices that the observed changes in total spending are entirely driven by quantity across the board. For example, there is no indication of suppliers reacting to the introduction of the reform by increasing prices in the last months of the old regime.[15] With this result at hand, we decompose the total change in quantity (*DDD*) into a) number of visits to the pharmacy and b) average quantity bought, conditional on purchase. We document that the consumers of pharmaceuticals react in both dimensions, but especially by buying more on each visit.

Finally, Table 3 investigates whether the regime switch is associated with delays in the timing of the next purchase. This must be the case in order for there to be a realized income effect of the observed stockpiling. On average, we see a 15% increase in time until next pharmacy visit (corresponding to about 19 days) when comparing February 2000 to February 1999. A delay in the days until the next pharmacy visit might obviously be due to stockpiling or may be a pure effect of the coinsurance rate increase. Interestingly, however, we find particularly large delays for groups who stockpile more and have more predictable demand, such as senior citizens and those who purchase one or two drugs treating chronic conditions. We also see individuals with lower predicted health delay their next purchase more than others—but again, the top 1% with the worst predicted health act differently than other individuals in the top 25%: their reaction to the reform is of smaller scale and there is no delay in their subsequent purchases. Part of the explanation is probably that they buy more frequently to begin with. Interesting also is the limited degree to which consumers buying three or more chronic drugs manage to postpone the onset of their first post-reform coverage year (5.6 days) despite buying 86% more *DDD*s in February 2000 than a comparable consumer in February 1999. This could potentially be explained by the fact that they appear to be stockpiling comparatively more of their expensive prescription drugs (but not the drugs with a lower coinsurance rate, cf. the two actuarial values in Table 2), as the value of the basket bought is up by 101% compared to the 86% increase in the number of *DDD*s. Finally, while there was no difference across income groups in the percentage increase in spending between February 1999 and 2000, there is a marked tendency for higher income individuals to be relatively less likely to delay subsequent purchases. This is possibly because they are healthier and experience long time spans between purchases. Pre-reform upticks in spending are then more likely tied to distinct episodes of illness instead of chronic disease.

[15] Alpert (2016) shows that there were no signs of drug companies changing prices before Medicare Part D was rolled out and argues that this might be because of the potential risk of political backlash.

TABLE 3

UNDERLYING AND SUBSEQUENT BEHAVIOR

	Laspeyres' Price Changes	Laspeyres' Quantity Changes	Change in DDD bought	Change in Fraction with purchase	Change in average DDD bought | purchase	Mean days until next purchase Feb 1999	Change in days until next purchase
All	0.00	0.82	0.76	0.19	0.49	124	0.15
Women	0.00	0.81	0.75	0.19	0.47	106	0.19
men	-0.01	0.84	0.78	0.18	0.51	152	0.12
Income quartile 1999							
Q1	0.00	0.82	0.76	0.18	0.49	85	0.23
Q2	0.00	0.82	0.77	0.19	0.48	111	0.17
Q3	-0.01	0.82	0.77	0.19	0.49	155	0.12
Q4	-0.01	0.81	0.75	0.18	0.48	184	0.10
Age							
< 30	-0.01	0.76	0.55	0.07	0.45	265	0.08
30-64	-0.01	0.81	0.78	0.19	0.50	145	0.15
> 64	0.00	0.83	0.76	0.21	0.45	61	0.32
Predicted health index quartile							
Q1	0.01	0.33	0.22	0.02	0.20	505	0.07
Q2	0.02	0.26	0.24	0.04	0.19	362	0.12
Q3	0.01	0.65	0.77	0.28	0.38	136	0.29
Q4	0.00	0.90	0.79	0.19	0.50	49	0.33
Top 1%	0.02	0.64	0.51	0.03	0.47	36	-0.14
#Chronic drugs taken							
0	0.01	0.18	0.18	0.01	0.18	240	0.21
1-2	-0.01	0.92	0.83	0.30	0.40	61	0.45
3+	-0.01	1.01	0.86	0.25	0.49	40	0.14

Notes: The predicted health index is the predicted consumption of prescription drugs in 1999 (2000) based on 1998 (1999) demographics, consumption, and other medical service use (see Appendix C for details). Chronic drugs are defined as drugs that the median consumer buys more than twice during a calendar year (see Appendix B). For all categories, the population is allowed to change age group, quartiles, and chronic status between February 1999 and February 2000. Own calculations based on total prescription drug spending in Denmark in 1999 and February 2000.

IV. Behavior within the non-linear plan

Having described how consumers appear to react to the introduction of the reform by stockpiling and consequently delaying post-reform purchases, we proceed to our main analysis that investigates how consumers react to the re-zeroing of accounts at the end of the coverage year and the associated sharp increase in spot price. We start with graphical evidence of the behavior to document its existence, extent, and nature. We then move to an econometrics analysis that exploits pre- and post-reform data in a difference-in-difference setup.

IV.A Descriptive evidence

Evidence across all drug types

Figure 4A depicts a sharp increase in total spending during the last days of the first post-reform coverage year and a subsequent decrease in the first weeks following the reset. We interpret this as compelling evidence that drug spending behavior responds to the incentives created by the resetting of the non-linear health insurance contract. One could rationalize a gradual spending increase throughout the coverage year with reference to the mechanical reduction in out-of-pocket costs caused by the insurance plan, but a sudden peak cannot be explained by a smooth decrease in coinsurance rates and a response to the spot price alone. The response size is considerable: spending during the last days of the coverage year is more than 40% higher than spending nine months into the coverage year.[16] We contrast the post-reform total expenditures with those of a pre-reform period where we apply the post-reform coverage measure on purchases. To align seasonal patterns in medical purchases pre- and post-reform, we make use of synthetic coverage years starting in March 1998; to avoid behavioral responses coming from the reform we only depict pre-reform coverage years that end before or in December 1999. Total spending clearly increases over time, causing a parallel upward shift in post-reform spending, but purchasing behaviors in within-coverage years do not otherwise change with the reform. The only important differences are the large increases in spending toward the end of the post-reform coverage year and the subsequent decreases after reset.

Next, Figure 4B shows the corresponding average coinsurance rates, conditional on purchase, again in contrast to the pre-reform period. This is the day-to-day variation in on-the-spot coinsurance rates. As expected, we observe a large increase in the coinsurance rates associated with purchases on the last day of the post-reform coverage year and purchases on the next day (for those who initiate a new coverage year immediately after the resetting). Pre-reform coinsurance rates are largely independent of the time since initiation of the coverage year, except for a slightly higher-than-average rate at

[16] Again, recall that many Danes carry supplemental insurance that reduces stockpiling incentives.

entrance. Individuals with acute but non-life-threatening illnesses who were therefore met with higher coinsurance rates (cf. Table 1) cause this pattern.

The increase in total spending may stem from several sources, including those listed in Table 3. Figure 4C depicts the associated development in mean total spending conditional on purchase: individuals clearly spend more money when they visit the pharmacy toward the end of the coverage year. This is driven by consumers purchasing larger quantities of similar products (4D).[17] We also see a clear increase in the number of visits (4E), and these visits were brought forward in time before the reset (4F).[18]

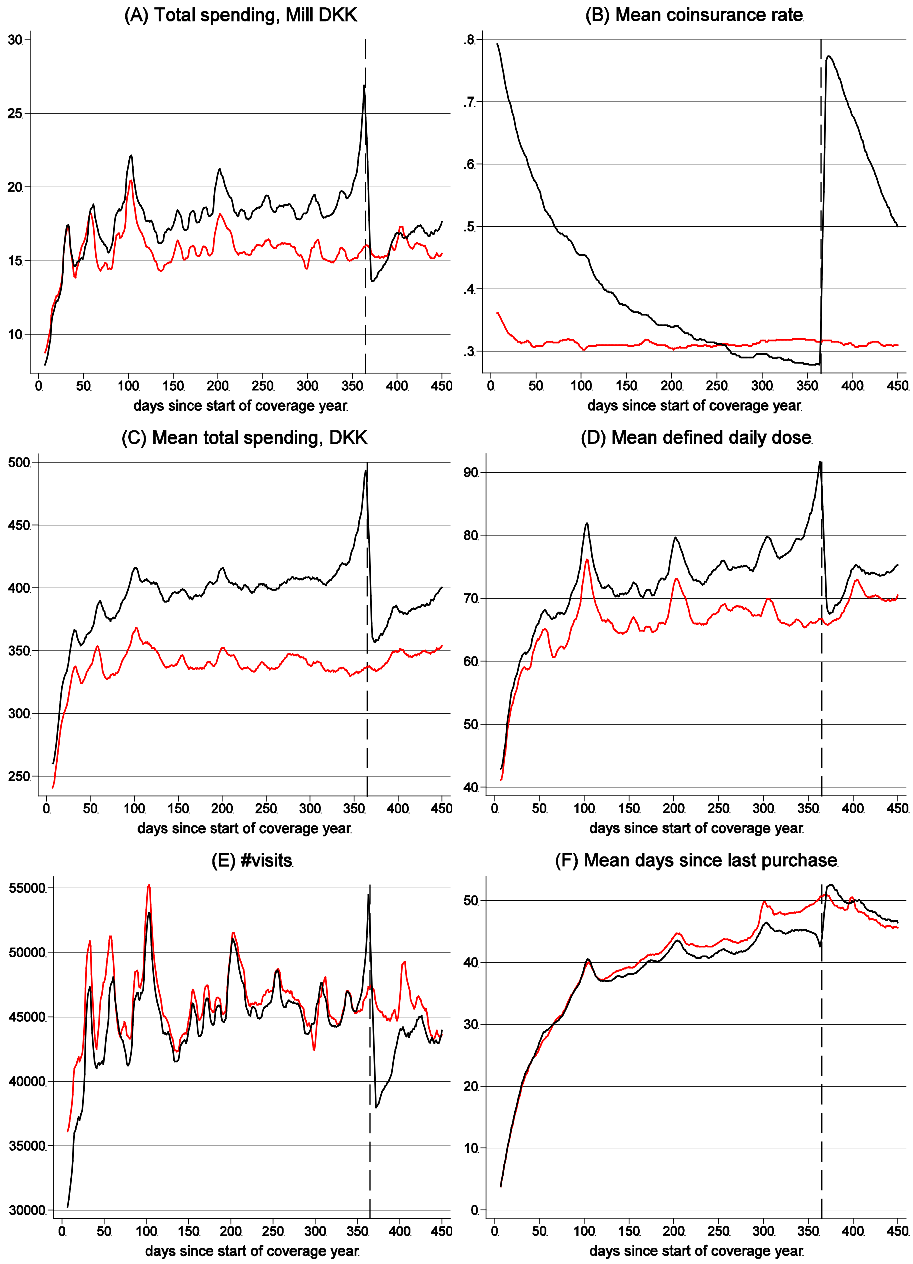
Evidence by drug type

Some types of demand are undoubtedly more predictable than other types, which we expect to affect stockpiling. Figure A5 in the Appendix shows the purchase patterns (mean *DDD* conditional on purchase and total *DDD*) for all drugs as a baseline and across drugs targeting chronic and non-chronic conditions (henceforth: chronic and non-chronic drugs). Conditional on purchase and in absolute value, individuals stockpile more chronic drugs compared to the level of purchases around coverage month nine. Relative to month nine, however, stockpiling does not vary across the two types of drugs. This is likely because of co-morbidities: patients suffering from chronic disease are also more likely to encounter other adverse health shocks. Similar patterns are found when considering the total volume in terms of *DDD*.

[17] Again, consumers might have reacted by buying more expensive brand name drugs. We do not find evidence of this in terms of increases in shelf prices (see Figure A4).
[18] We were unable to analyze time similarly since the last purchase in the pre-reform setting because of the lack of a natural anchoring point (here start of coverage year).

FIGURE 4

PURCHASING BEHAVIOR, PRE- AND POST-REFORM



Notes: This figure presents evidence of individual behavioral responses to the end-of-year reset. The thick black line is post-reform, gray (red if read online) is synthetic pre-reform. The vertical dotted line separates days into current and next coverage year. (B), (D), (E), and (F) are all measured conditionally on purchase. All prices are nominal ignoring (pharmaceutical) inflation. Pre-reform data shows synthetic coverage years constructed based on first purchases March–October 1998; the post-reform data uses first coverage year initiated March–October 2000. To smooth out the day-of-week difference, an MA(7)-process is imposed on the daily data. First day in coverage year excluded from graph.

Figure A6 focuses instead on specific drug types, defined by ATC codes,[19] with clear and varying characteristics: 1) diabetes medications, 2) phenoxymethylpenicillin (penicillin V), which is a narrow-spectrum antibiotic, and 3) opioids prescribed to relieve severe and chronic pain. We hypothesize that individuals stockpile diabetes medications but not penicillin V. We expect some stockpiling of opioids because of their use for chronic disease[20] but to a limited extent, since opioids are highly addictive.

Individuals clearly stockpile diabetes medications—which we observe both in terms of dose conditional on purchase and total purchases. Conversely, doses of penicillin V prescribed conditional upon purchase are practically flat across the coverage year, with no end-of-coverage-year peak. It is worth noting how there is within-coverage-year seasonality in total doses: those who initiate their coverage year with purchases of penicillin V to treat a light bacterial infection face an increasing probability of being hit again from about 150–300 days later. We find little end-of-year increase, however. As expected, we only see a slight (one dose) end-of-year response for opioids conditional upon purchase as well as a small reaction in terms of total doses prescribed.

The role of the prescribing physicians

Clearly, the observed end-of-year responses cannot take place without a prescription from a physician and, thus, without their implicit consent. Although not prohibited by law, some physicians may be more or less prone to endorse and cooperate with this behavior. To obtain a sense of variation across physicians, we shift the analysis to be at the physician level. For each prescribing physician, we then calculate the value of their total coverage month 12 prescriptions and compare this to the value of their month nine prescriptions. Figure 5 shows the resulting distributions from this exercise.

If anything, physicians prescribe slightly less in (synthetic) coverage month 12 compared to month nine prior to the introduction of the non-linear plan. This is actually also reflected in the individual-level spending (see Figure 4E above) and is possibly due to mean reversion in health: some patients will remain in poor health throughout the coverage year, of course, but some will improve. Yet after the introduction of the non-linear plan we see a stark shift in physician behavior; in fact, more than 95% of physicians now prescribe *more* in month 12 than in month nine. We observe important

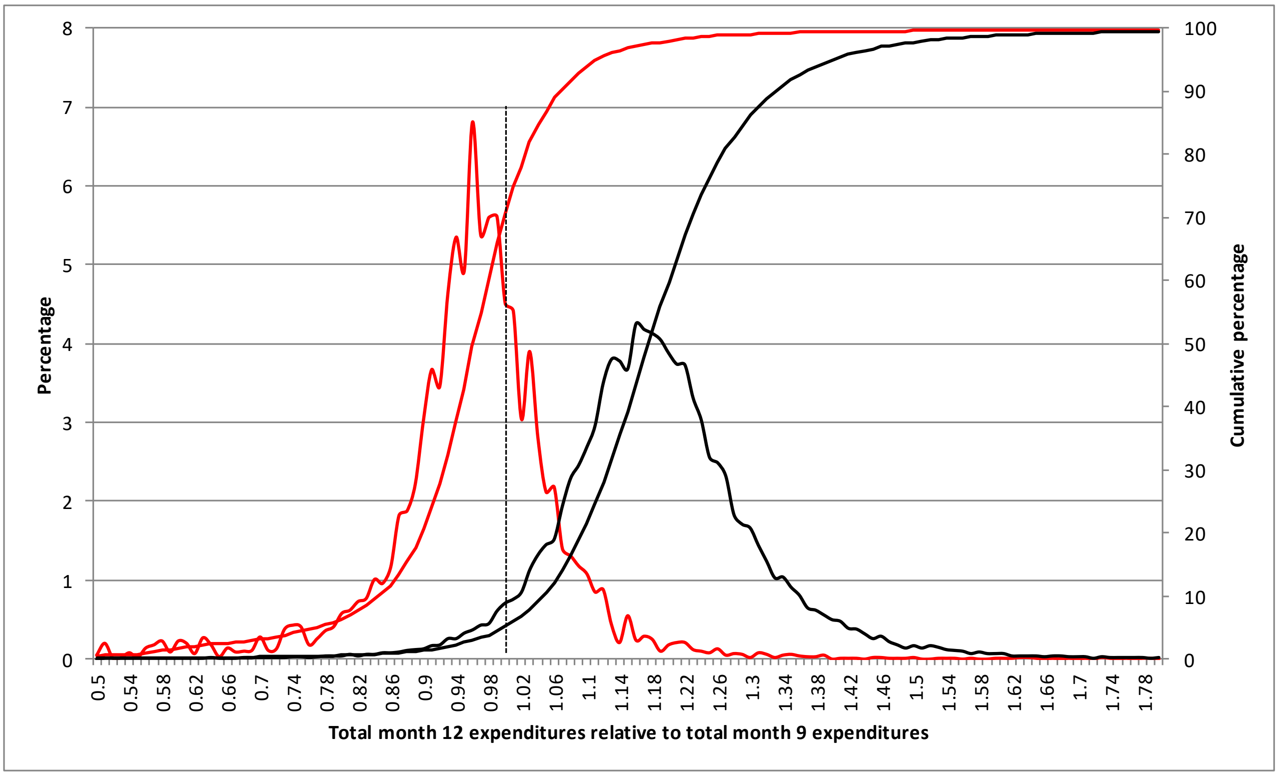
[19] Anatomical Therapeutic Chemical is a classification under the WHO that divides drugs into groups depending on the organ or system that they target (see https://www.whocc.no/atc/structure_and_principles/).

[20] It is, in fact, among the drugs most often prescribed to diabetics.

variation in physicians' prescribing behavior; about 5% of physicians, for example, prescribe more than 40% more in month 12 relative to month nine.[21]

FIGURE 5

TOTAL SPENDING ASSOCIATED WITH PHYSICIANS' PRESCRIPTIONS, COVERAGE MONTH 12 RELATIVE TO MONTH 9



Notes: This figure shows the total prescription drug spending associated with physicians' prescriptions in coverage month 12 relative to month 9 (left axis) and cumulative percentage, weighted by number of prescriptions. The thick black line is post-reform, gray (red if read online) is synthetic pre-reform. The figure excludes physicians prescribing to fewer than ten patients per year. Sample years cover 1998–2014.

IV.B Reaction to end-of-year reset: formal analyses

We now formally evaluate the reaction to the end-of-year reset with the associated sudden increase in tomorrow's spot price. The formal econometric analysis also allows us to parsimoniously

[21] To explore the degree to which patient composition explains variations in physician stockpiling behavior, we regress coverage month 12 relative to coverage month nine prescriptions on patient characteristics corresponding to the variables included in the descriptive analysis shown in Table 2 (the share of men; the share in each income quartile; the share in each age category 18–30, 30–64, and > 64; the share in each lagged spending quartile; and the share in each chronic drug category 0, 1–2, and above 2) as well as clinic size (number of patients, number of prescriptions in each year) and year dummies. This model explains as little as 0.6% of the variation in the outcome.

investigate heterogeneity in responses by individual patient characteristics as well as proxies for health status.

Obviously, the key challenge inherent in such an analysis is how to estimate spending choices in the absence of the end-of-year reset. Specifically, those who can meaningfully respond at the end of the coverage year are likely different than the average prescription drug consumers: they need to be in sufficiently poor health to be equipped with a prescription from their GP.

To address this, we implement a difference-in-differences strategy using individual-level panel data. This corresponds to a fixed-effects analysis. For feasibility reasons and in line with our pre-reform descriptive analyses, we group purchases at a monthly level. Our preferred strategy first compares one individual's purchase patterns toward the end of a coverage year with the same individual's purchase patterns earlier in the coverage year. This first difference implicitly controls for time-invariant individual health and access to any supplemental health insurance; sources that would confound within- and across-individual correlations in purchasing and stockpiling behavior. However, it is possible that individual-level health changes over the course of the coverage year or that there is otherwise systematic variation in purchasing patterns across months. While there are no financial incentives for individuals to behave differently across months sufficiently long before the introduction of the non-linear plan, some drugs are clearly prescribed at a fixed cadence (see Figure 4). To address this, we make use of data prior to the introduction of the non-linear plan. Here, since coinsurance rates do not vary mechanically with time into the (synthetic) coverage year, a comparison of individual behavior in different coverage months therefore allows us to account for spending variation across coverage months that is unrelated to the insurance plan. Note that in our set-up, individuals *de facto* serve as their own controls both before and after the new plan.

As discussed above and as evident in Figure 4B, a second issue is that coinsurance rates (and therefore spot prices) in the non-linear insurance plan smoothly decline with accumulated purchases within a coverage year, which may make some individuals purchase more at later points in the coverage year. As pointed out by Aron-Dine et al. (2015), Dalton et al. (2015), and Brot-Goldberg et al. (forthcoming), the opportunity for consumers to react to spot prices is empirically relevant and possibly due to present biases, behavioral (cognitive and attention) biases, as well as liquidity constraints. A lower coinsurance rate, however, is a function of accumulated purchases within the coverage year and therefore likely correlates with health. In this sense, the coinsurance rate is endogenous to the underlying medical needs and not included in our main model. More importantly, a gradual decrease in coinsurance rates should *not* generate a discontinuous increase in purchases toward the end of the coverage year. To ensure that our main results are not driven by coinsurance rate variation, our primary robustness analysis replicates the difference-in-difference strategy while at the same time controlling for the entrance coinsurance rate in each coverage month. In pre-reform months, we condition on the average coinsurance rate of bundles bought in the previous months.

We choose coverage month nine as the reference month in our formal analyses. This serves two purposes: first, an ideal reference month resembles the coverage month immediately prior to the reset in terms of the type (or underlying health) of individuals making purchases as well as the type of purchases. Coverage month nine fulfills this requirement by being in close temporal proximity. Second, coverage month nine lies at the same time sufficiently early in the coverage year to minimize the risk of contamination due to an end-of-year-stockpiling response.[22]

Our main regression model allows behavior across coverage months to vary with the introduction of the non-linear plan. It also flexibly controls for time, both in terms of calendar and coverage months and with regards to calendar years and the number of coverage years initiated.[23] In practice, we estimate the following specification:

$$Y_{i,cm} = \alpha_i + \sum_{cm \in CM} \gamma_{cm} I_{cm} + \sum_{m \in M} \gamma_m I_m + \sum_{t \in T} \gamma_{ct} I_{ct} + \sum_{t \in T} \gamma_t I_t + \left[\sum_{cm \in CM} \delta_{cm} I_{cm} \right] I_{t_{post}} + \varepsilon_{it}$$

where Y is the outcome of interest, $I_{t_{post}}$ indicates post-reform periods, cm indicates each of the months in a coverage year (a synthetic coverage year if pre-reform; see above), ct indicates each of the post-reform coverage years, m indicates calendar months, and t the calendar years. Furthermore, α is an individual fixed effect (that flexibly captures the group effect in a standard repeated cross-sectional difference-in-difference analysis); ε is an idiosyncratic error term; *i* indexes individuals. δ_{12} is the parameter of interest and is informative about the extent to which individuals behave differently in the last month of the coverage year relative to the excluded month nine *after* the introduction of

[22] As shown in Appendix Figure A7, conclusions are qualitatively robust to choice of reference month.

[23] Immediately after the introduction of the non-linear plan, coverage years were more likely to start in March and April (see Appendix Figure A8). Though this tendency diminishes strongly over time, calendar month dummies in combination with calendar year indicators will also address this.

the reform. To allow for flexibility in the estimation of the variance–covariance matrix, we cluster the standard errors at the individual level.

We select a range of outcome variables to characterize purchasing behavior prior to reset: spending, number of visits to the pharmacy, spending conditional on purchase, volume, and days until next purchase. We truncate the latter at 365 days to ensure that individuals in either regime are observed equally long in our data. We expect this to be innocuous, since gaps of more than 365 days between purchases are much more likely to be driven by (a lack of adverse) health shocks than by strategic behavior. Our estimation data set consists of a 10% random sample of all of the individuals who initiate a coverage year in 2000–14. In addition, our control year consists of individuals who initiate a (synthetic) coverage year in 1998. Because individuals react by stockpiling immediately prior to the reform, we always exclude the two individual observation months prior to the reform (January–February 2000). Our final sample comprises roughly 500,000 individuals.

Table 4 presents our main results. We start with a model that only relies on post-reform data and then gradually modify the specification with the inclusion of individual-level fixed effects and pre-reform data. The last column shows results where we additionally condition on the coinsurance rate at the beginning of the coverage month. Importantly, our results are generally similar across specifications, qualitatively but also quantitatively. Focus first on the response during the last month of the coverage year. In line with the descriptive analyses, we estimate a large increase in spending per individual of 20% relative to month nine in our preferred specification. This is to some extent driven by an increase in the number of visits (10%) but to a greater extent by an increase in volume per visit (15%).

Time to next visit is extended slightly (5.4 days or 11%) on average. While this might seem low at the outset, to get a sense of how much stockpiling individuals postpone their next purchase as a consequence of their forward-looking behavior, one must up-weight this estimate by the share of stockpilers. A back-of-the-envelope calculation using the 20% increase in spending as a proxy for the share of stockpilers yields an estimate of the increase in time to next visit of roughly 27 days, corresponding precisely to our estimated increase in *Defined Daily Dose* conditional upon purchase; using the percentage increase in number of visits as a proxy instead gives 49 days. As argued above, the possibility of postponing the start of the next coverage year gives rise to an income effect: stockpiling prescription drugs allowing for treatment for 32 days implies that the consumer "saves" one coverage year every 13½ calendar years. Of course, the interpretation of the effects on the time to the next visit is less clear-cut after reset: a delay might be a consequence of stockpiling but may also be a direct effect of the sharp, sudden spot price increase at the beginning of the new coverage year.

TABLE 4

REACTION TO END-OF-COVERAGE-YEAR RESET (MONTH 12)

	# Observations # Individuals	Mean Post-reform Month 9	Coefficient Std. Error Pct. of mean	Coefficient Std. Error Pct. of mean	Coefficient Std. Error Pct. of mean	Coefficient Std. Error Pct. of mean
Spending (shelf price, DKK)	55,584,249	259	**49.13**	**50.51**	**52.09**	**46.61**
	523,045		0.65	0.54	1.84	1.84
			19%	19%	20%	18%
# monthly visits to pharmacy	55,584,249	0.606	**0.049**	**0.063**	**0.063**	**0.073**
	523,045		0.001	0.001	0.002	0.002
			8%	10%	10%	12%
Spending (shelf price, DKK) | purchase	24,752,965	642	**90.86**	**100.00**	**100.79**	**85.72**
	523,045		1.42	1.13	4.07	4.05
			14%	16%	16%	13%
Volume (DDD) | purchase	24,752,965	139	**20.41**	**21.64**	**20.34**	**19.61**
	523,045		0.18	0.14	0.52	0.52
			15%	16%	15%	14%
Days until next purchase | purchase	24,752,965	48	**4.64**	**3.20**	**5.42**	**5.91**
	523,045		0.06	0.05	0.20	0.20
			10%	7%	11%	12%
Post-reform data only			X	X		
Individual level FE				X	X	X
Co-insurance rate primo each month						X

Notes: Difference-in-difference estimation based on a 10% random sample of individuals making at least one purchase in the observation window. Excluded coverage month is month 9. “Days until next purchase” is truncated at 365 days. Standard errors clustered at individual level. Bold indicates significance at the 5% level. Sample years cover 1998–2014.

V. Robustness analyses

V.A Heterogeneity in responses

The first section in Table 5 investigates the extent to which end-of-year responses vary with individual-level characteristics. Men and women tend to stockpile similarly, but we observe interesting variations across the income and age distributions. Individuals in the two lowest income quartiles stockpile less than others. This might be because they face lower coinsurance rates due to other public means-tested subsidies[24] but might also be due to credit constraints. Conversely, individuals in the third income quartile react by far the most to the end-of-year reset. Young individuals generally buy fewer prescription drugs and react correspondingly less to the reset. Those aged 30–64 react most strongly to the reset, while the oldest part of the population reacts slightly less. Again, this may be driven by a combination of means-tested subsidies and credit constraints.[25]

The next part of Table 5 shows heterogeneity in results by predicted consumption of prescription drugs and previous chronic drug use. The healthiest (in terms of predicted consumption) individuals do not react toward the end of the coverage year at all; their estimates are limited in size and insignificant. Conversely, individuals with predicted spending in the third and fourth quartiles react strongly. Individuals buy more in the last month of the coverage year regardless of their previous use of chronic drugs but those who consume at least one chronic drug do this the most. Note that while there is certainly persistence in health-care spending over time (Hirth et al., 2016), there is still substantial mean-reversion in health; some of those who do not suffer from chronic disease one year ago will do so today—this might explain some of the excess purchases we see even among individuals who do not consume what we classify as chronic drugs.

[24] 25% of the individuals in the lowest income quartile (Q1) receive additional subsidies compared to 10% of those in Q2, 0.1% of those in Q3, and none in Q4. Conditional on receiving additional subsidies, these cover on average 75–90% of the amount not covered by the universal non-linear plan.

[25] 1% of the individuals under age 30 receive additional subsidies compared to 4% of those aged 30–64 and 24% of those 65 and older.

TABLE 5

REACTION TO END-OF-YEAR RESET (MONTH 12): DIFFERENCE-IN-DIFFERENCE RESULTS EVIDENCE ACROSS INDIVIDUAL-LEVEL CHARACTERISTICS AND HEALTH

	Spending (shelf price, DKK)	Spending (shelf price, DKK) | purchase
	Coefficient	Coefficient
	Std. Error	Std. Error
	Pct. of mean	Pct. of mean
Women	**51.69**	**94.07**
	2.34	4.96
	20%	15%
Men	**52.17**	**107.71**
	2.96	6.97
	21%	16%
Income quartile		
Q1	**64.081**	**100.688**
	3.455	6.233
	18%	14%
Q2	**61.590**	**113.224**
	3.853	8.002
	20%	16%
Q3	**47.193**	**103.718**
	3.690	9.198
	25%	19%
Q4	**36.803**	**90.957**
	3.277	9.233
	22%	17%
Age		
< 30	**10.51**	**43.24**
	4.06	17.24
	10%	8%
30-64	**51.31**	**112.70**
	2.48	6.06
	23%	18%
> 64	**77.80**	**98.29**
	3.45	5.20
	19%	15%
Individual level FE	X	X

Notes: Difference-in-difference estimation based on a 10% random sample of individuals making at least one purchase in the observation window. The excluded coverage month is month 9. Standard errors clustered at individual level. Bold indicates significance at the 5% level. Characteristics measured in calendar year prior to coverage year initiation. Sample years cover 1998–2014.

TABLE 5 CTND.

REACTION TO END-OF-YEAR RESET (MONTH 12): DIFFERENCE-IN-DIFFERENCE RESULTS EVIDENCE ACROSS INDIVIDUAL-LEVEL CHARACTERISTICS AND HEALTH

	Spending (shelf price, DKK)	Spending (shelf price, DKK) | purchase
	Coefficient	Coefficient
	Std. Error	Std. Error
	Pct. of mean	Pct. of mean
Predicted health index quartile		
Q1	-0.61	-17.82
	2.21	22.85
	-3%	-9%
Q2	-0.20	-5.38
	0.63	4.91
	-1%	-4%
Q3	**12.88**	**22.21**
	0.87	2.48
	20%	11%
Q4	**115.78**	**132.00**
	2.98	3.85
	23%	18%
Top 1%	**483.80**	**531.31**
	78.81	78.87
	16%	15%
#Chronic drugs taken		
0	**14.24**	**43.98**
	1.73	1.73
	20%	13%
1-2	**62.65**	**89.39**
	3.06	5.10
	25%	17%
3+	**173.20**	**180.05**
	10.04	11.68
	26%	20%
Individual level FE	X	X

Notes: Difference-in-difference estimation based on 10% random sample of individuals making at least one purchase in the observation window. The excluded coverage month is month 9. Standard errors clustered at individual level. Bold indicates significance at the 5% level. Characteristics measured in calendar year prior to coverage year initiation. The predicted health index quartiles classify consumers in terms of the predicted consumption of prescription drugs based on previous consumption and use of other medical services in the 365 days leading up to coverage year initiation (see Appendix C). Chronic drugs are defined as drugs purchased more than twice in a calendar year by the median consumer (see Appendix B). Sample years cover 1998–2014.

Table 6 instead quantifies heterogeneity by types of drugs. As in the descriptive analyses, we focus on the purchase of drugs with highly predictable demand (diabetes medications), a drug associated with less severe but acute disease (the narrow-spectrum antibiotic penicillin V), and addictive drugs prescribed for severe and chronic pain (opioids). The formal analyses confirm the descriptive results for diabetes meds, primarily in terms of total volume but also for volume conditional on purchase, indicating that more diabetics visit the pharmacy and they buy more than the usual amount. The model detects a smaller end-of-year response for penicillin V, but this is driven by more individuals picking up a prescription and not by higher prescribed doses. We estimate a 7% increase in the total volume of opioids prescribed toward the end of the year and a one dose increase in volume conditional upon purchase.

TABLE 6

REACTION TO END-OF-COVERAGE-YEAR RESET (MONTH 12):

DIFFERENCE-IN-DIFFERENCE RESULTS, EVIDENCE BY TYPES OF DRUGS

	Antidiabetic[a]	Phenoxymethylpenicillin[b]	Opioids[c]
	Coefficient	Coefficient	Coefficient
	Std. Error	Std. Error	Std. Error
	Pct. of mean	Pct. of mean	Pct. of mean
Volume (*DDD*)	**0.560**	**0.020**	**0.064**
	0.036	0.005	0.015
	23%	10%	7%
Volume (*DDD*) | purchase	**10.527**	-0.009	**1.374**
	1.045	0.084	0.408
	14%	0%	5%
Individual level FE	X	X	X

Notes: 10% random sample of individuals making at least one purchase in the observation window. Standard errors clustered at individual level. Bold indicates significance at the 5% level. Sample years cover 1998–2014.

[a] ATC code: A10. [b] ATC code: J01CE02. [c] ATC code: N02A.

V.B Heterogeneity by experience

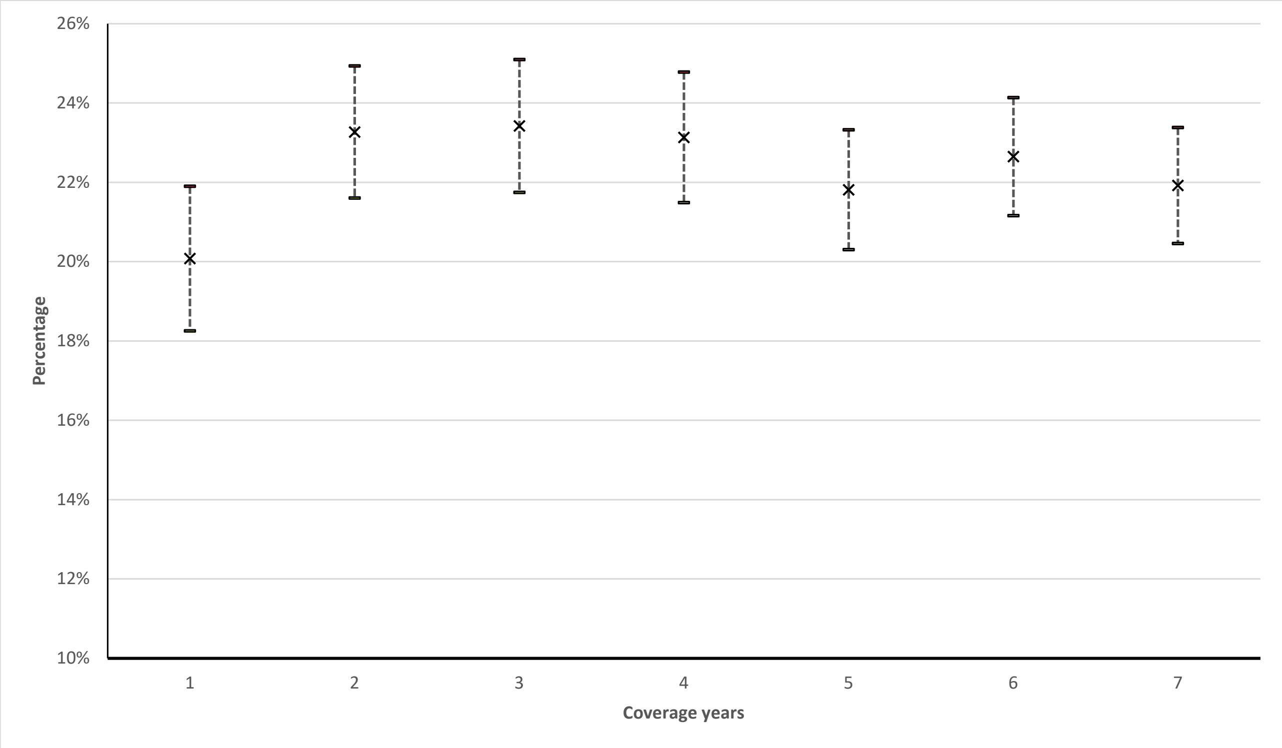
Some consumers possibly do not react toward the end of the coverage year, even if they are meaningfully able to do so, because they do not fully comprehend the details of and subtle incentives inherent in the plan. To get a sense of the degree to which the details inherent in the non-linear plan seem complicated to users, we quantitatively investigated the debate surrounding the reform. Specifically, we used the Danish newspaper search engine *Infomedia* and searched for “prescription drug subsidies,” “prescription drug rules,” and “prescription drug scheme” (in Danish: *medicintilskud*, *medicinregler*, and *medicinordning*). We limited our search to the eight nationwide newspapers.[26] This search produced as many as 176 unique hits in the period January 1, 1999–April 30, 2000. Among these, 13 (7%) mentioned the words “complicated” or “complex” (in Danish: *kompliceret* or *indviklet*). Literacy issues have been shown to arise within choice of health care plan (e.g. Kling et al. (2012)), financial decision-making (e.g. Lusardi and Mitchell (2007) and Drexler et al. (2014)), and tax-filing (Chetty and Saez (2013)).

Next, we investigate whether experience with and thus knowledge of the non-linear plan increases the tendency for individuals to buy more immediately prior to reset but also the extent to which consumers delay the time to the next purchase. In practice; we repeat our estimation strategy from above for groups of individuals who have initiated at least x coverage years and consider their behavior (tendency to buy more toward the end of the coverage year; time to next purchase) in coverage year x. We arbitrarily cap the analysis at eight coverage years—individuals who initiate more coverage years during our 14-year data window have, by construction, allowed for very little time between each coverage year. As shown in Figure 6, we find slight evidence that experience increases stockpiling slightly before reset at low levels of experience, but we see no increase in the deferment of subsequent coverage year initiation; see also Brot-Goldberg et al. (forthcoming). Three explanations prevail: consumers might face (time invariant) restrictions from physicians, there might in fact only be little learning over time, and/or their initial responses are simply optimal.

[26] Aktuelt, Berlingske, BT, Ekstrabladet, Information, Jyllandsposten, Politiken, and Weekendavisen.

FIGURE 6A

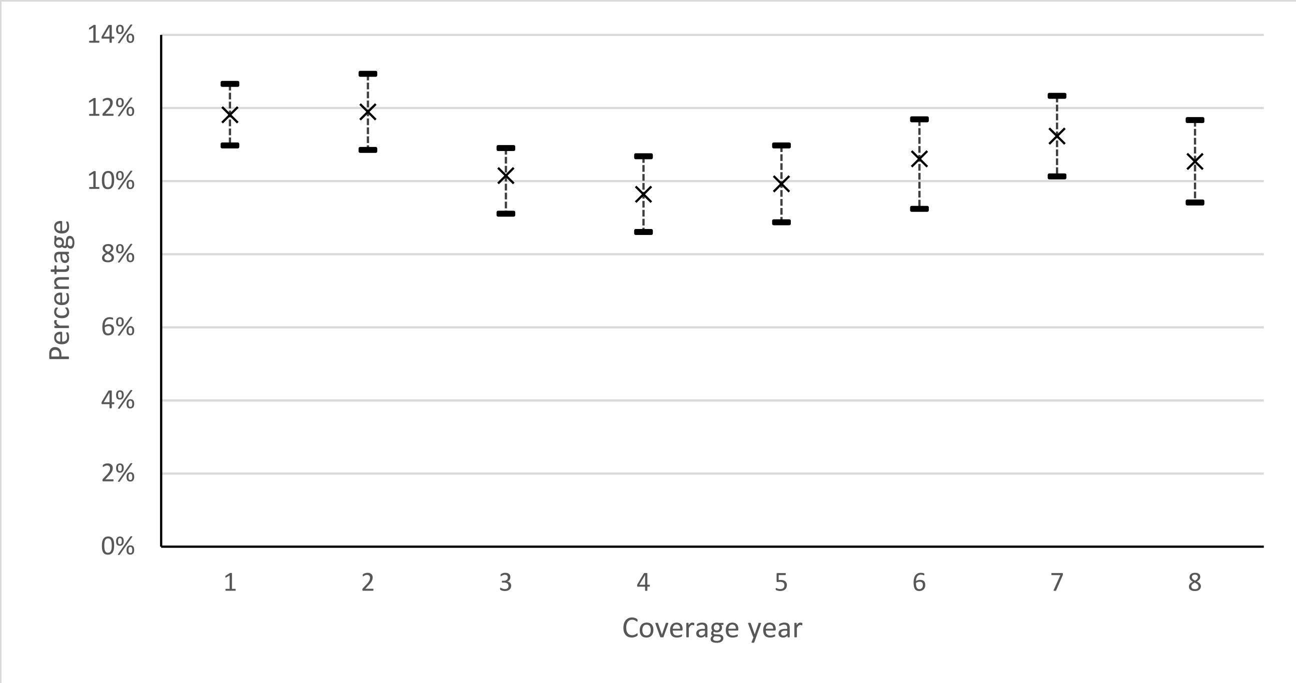
REACTION TO END-OF-COVERAGE-YEAR RESET (MONTH 12), ACROSS COVERAGE YEARS PERCENTAGE INCREASE IN SPENDING (SHELF PRICE, DKK)



Notes: This figure shows estimated tendencies and 95% point-wise confidence bounds for individuals to spend more immediately prior to reset (version not conditional on purchase) across coverage years. Difference-in-difference estimation with individual-level FE as in Table 4 for groups of individuals who have initiated at least *x* coverage years, with estimated behavior in coverage year *x*. Sample years cover 1998–2014.

FIGURE 6B

REACTION TO END-OF-COVERAGE-YEAR RESET (MONTH 12), ACROSS COVERAGE YEARS PERCENTAGE INCREASE IN DAYS UNTIL NEXT PURCHASE | PURCHASE



Notes: This figure shows percentage increases in estimated time in days until next purchase (or coverage year initiation) as a percentage of mean days in month 9 along with 95% point-wise confidence bounds across coverage years. Difference-in-difference estimation with individual-level FE as in Table 4 for groups of individuals who have initiated at least *x* coverage years, with estimated behavior in coverage year *x*. Sample years cover 1998–2014.

VI. Effects on health care utilization and health outcomes

It is theoretically unclear how the introduction of the nonlinear prescription drug plan and the end-of-year reset will impact health care utilization and, ultimately, health outcomes—if at all. Remember that health care is generally free of charge for Danish residents. While individuals may approach their GPs more often in the period leading up to the reform or reset in order to fetch a prescription, we might also see many or fewer interactions (and services) if consumers bundle purchases on fewer prescriptions. From a welfare and public finance perspective, an increase in the use of GPs is costly but we may also worry about the adverse health consequences of a potential overdose or addiction directly lowering consumer welfare (see Powell et al. (2015) on ease of access to opioids and the opioid epidemic).

To address these questions, we analyze a series of additional variables, namely interactions with one's GP; fee-for-service paid to GP; indicators for hospitalization and for hospitalization due to drug poisoning and other adverse effects. Because some of these outcomes are rare events, we return to the full population data set.

Table 7 shows health care use in February 2000 leading up to the introduction of the non-linear plan relative to that of February 1999. We see some uptick in interactions with GPs and the associated fee-for-service but not to an extent comparable to the 80% increase in purchases (interactions with the GP regarding renewal of prescriptions only as GPs do not receive a fee for this service). There is hardly any change in the number of individuals with hospital interactions. Poisoning is a very rare event (0.3% of hospital interactions in February 1999), and there is basically no difference between the share of hospital interactions due to poisoning in February 1999 and February 2000 (0.300 versus 0.295%).

TABLE 7

HEALTH CARE USE LEADING UP TO INTRODUCTION OF THE NON-LINEAR PLAN

	Feb 1999	Feb 2000	Change from Feb 1999 to Feb 2000
GP interactions:			
# individuals with at least one interaction with GP	1,244,954	1,277,734	0.026
Total fee-for-service (DKK)	185,694,121	195,903,253	0.055
Hospital interactions:			
# individual with at least one hospital interaction	242,277	239,993	-0.004
… # due to poisoning by drugs[a]	727	708	-0.026
… plus # other adverse effect of drug[b]	894	914	0.022

Notes: Full population of individuals making at least one purchase in the observation window. Own calculations based on full population in February 1999 and February 2000.

[a] ICD-10 codes T36-T50

[b] ICD-10 codes T88.6, T78.2, T78.4, T78.8, T78.9, and T88.7

Table 8 continues to formally analyze health use effects associated with the end-of-year reset. Again, we find no adverse health care use consequences; in a financial sense, we estimate a slight fall in the number of interactions with one's GP with an associated decrease of a little less than €1in fee-for-service. Estimates for hospital-related measures are insignificant regardless of the outcome under consideration and we can reject even small increases.

TABLE 8

REACTION TO END-OF-COVERAGE-YEAR RESET (MONTH 12): DIFFERENCE-IN-DIFFERENCE RESULTS, HEALTH CARE USE

	# Observations # Individuals	Mean Post-reform Month 9	Coefficient Std. Error Pct. of mean
Interaction with GP (0/1)	568 mill. 5.16 mill.	0.396	**-0.0094** 0.00037 -2%
Fee-for-service to GP (DKK)	568 mill. 5.16 mill.	82.51	**-6.310** 0.140 -8%
Hospital interaction (0/1)	568 mill. 5.16 mill.	0.0630	-0.000477 0.000197 -1%
Hospital interaction due to poisoning by drugs (0/1)	568 mill. 5.16 mill.	0.0002	-0.000003 0.000012 -1%
Hospital interaction due to any adverse effects of drug (0/1)	568 mill. 5.16 mill.	0.0003	0.000004 0.000014 1%
Individual level FE			X

Notes: Full population of individuals making at least one purchase in observation window. Standard errors clustered at individual level. Bold indicates significance at the 5% level. Sample years cover 1998–2014.

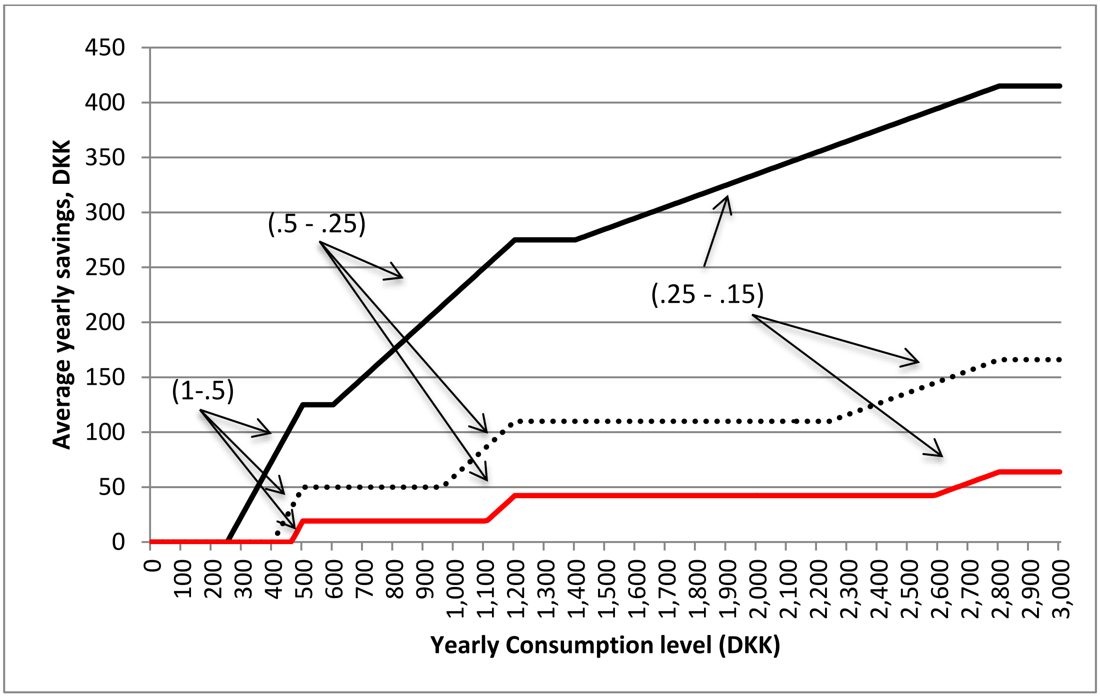
VII. Gains associated with observed behavior

We saw above that individuals were considerably more likely to purchase immediately prior to reset, indicating that they realize a benefit from such behavior. Yet we detect only a very weak link between prior experience with the nonlinear plan and the extent of stockpiling. To further explore and rationalize these findings, this section probes the gains from the observed behavior.

One way to approach the question of stockpiling-associated gains in the non-linear plan is to calculate them directly in a stylized set-up with perfect foresight (similarly to Figure 3), with prescription drug spending needs held constant and no discounting. Figure 7 shows the results from this exercise for three different levels of stockpiling. For the segments with positive slopes, the differences reflect changes in the coinsurance rates over the relevant expenditure range. As expected, monetary gains increase with yearly consumption, measured in terms of accumulated total expenditures evaluated at shelf prices and with the share one stockpiles. Gains can be considerable in size if the stockpiled amount is sufficiently large. Our estimates from the difference-in-difference analysis above, however, suggest that those who stockpile on average increase the time to the next visit in the order of 30–50 days; Figure 7 shows that an individual who stockpiles a month's supply of drugs saves between DKK 0–60 (€0–9) for yearly (fixed) consumption levels between DKK 0–3000 (€0–400). Even where this is non-negligible compared to the out-of-pocket costs associated with yearly consumption—someone with yearly accumulated expenditures of DKK 500 will, for example, save 5% from stockpiling a month's worth of drugs—it is still a rather small amount. If the *amount* of stockpiling is usually determined by the GPs and the gains are small in an absolute sense, regardless of one's income level, this may contribute to explaining why stockpiling is still rather limited and why there is little change over time.

FIGURE 7

MONETARY GAINS FROM STOCKPILING IN NON-LINEAR INSURANCE PLAN: STYLIZED SET-UP WITH PERFECT FORESIGHT



Notes: This figure shows monetary gains by yearly consumption levels from stockpiling the value of one year's consumption (black), a quarter of a year's consumption (black, dashed), and one month's consumption (gray, red if read online). The analysis assumes perfect foresight, constant health, and no discounting. Yearly consumption level measured in terms of accumulated total expenditures evaluated at shelf prices. For the segments with positive slopes, the differences stem from changes in the coinsurance rates from stockpiling over the relevant expenditure range (cf. Figure 3).

Note also that one can think of the monetary gains presented in Figure 7 as upper bounds; uncertainty concerning actual future needs, deterioration of health, drug patents expirations, shelf price volatility, and the introduction of cheaper or more effective drugs with fewer side effects should all reduce the willingness to buy in bulk. Exceptions are cases where individuals suffer from temporary and unforecastable flare-ups or acute disease—they should all attempt to concentrate their purchases within the same coverage year.

Another way of exploring gains exploits the observation that for individuals nearing the end of the coverage year, the current plan (coverage year) dominates the future plan when the marginal price (spot price) is strictly lower than the expected out-of-pocket fraction inherent in the future plan—and stockpiling offers a way to remain in the current plan. To gauge the share of individuals for whom this is true, again assuming perfect foresight, we compare the coinsurance rate associated with the last purchase in a coverage year with the average out-of-pocket shares of total expenditures (or 1 minus the actuarial value) associated with the subsequent coverage year based on *realized* purchases. This obviously includes the possibility that stockpiling might have brought down the spot price for individuals close to but below one of the three coinsurance thresholds—and makes stockpiling appear more attractive than it is. Table 9 illustrates the results from this exercise.[27] Individuals who spent under the deductible clearly stand little to gain from stockpiling. This changes as spending increases, both in terms of the fraction with a positive gain (spot price < 1 minus the actuarial value in subsequent coverage year) and in terms of the actual difference between the spot price and future out-of-pocket share. Given that one spends over the deductible, the vast majority will benefit from buying as much as possible in the current plan/coverage year. Importantly, about 40% of all consumers spent under the deductible in 2000; yet because the system was made more progressive (cf. Figures A1 and A2), this increased to 50% in 2010. *De facto*, stockpiling has become attractive for an ever smaller share of the population. This might be another explanation for the lack of increase in stockpiling with experience with the non-linear plan.

[27] In this analysis, we should ideally know which time horizon is relevant to consumers. Here, we choose a six-month outlook. Thus, we censor the actuarial value at zero for all consecutive coverage years where there is more than six months between completion and initiation of a new coverage year.

TABLE 9

END-OF-COVERAGE-YEAR SPOT PRICE VERSUS ACTUARIAL VALUE OF SUBSEQUENT PLAN, BY REALIZED SPENDING DECILES

Spending decile	Mean end-of-year coinsurance rate		Mean gain from stockpiling		Fraction with positive gain		Median days until onset of new coverage year	
	2000	2010	2000	2010	2000	2010	2000	2010
1	0.99	0.98	-0.02	-0.03	0.02	0.03	> 365	> 365
2	0.98	0.98	-0.03	-0.02	0.02	0.03	311	233
3	0.98	0.97	-0.04	-0.02	0.03	0.03	226	135
4	0.96	0.96	-0.06	-0.03	0.05	0.04	146	77
5	0.60	0.93	0.21	-0.04	0.81	0.12	88	50
6	0.43	0.53	0.25	0.27	0.83	0.87	53	38
7	0.25	0.29	0.27	0.38	0.89	0.93	39	30
8	0.18	0.21	0.22	0.30	0.90	0.93	31	24
9	0.15	0.16	0.15	0.21	0.89	0.93	26	20
10	0.14	0.13	0.08	0.12	0.83	0.89	17	14

Notes: Calculations are based on all individuals initiating a coverage year in 2000 or 2010. The gain from stockpiling is calculated based on a comparison of realized, end-of-year spot price in year t with one minus realized actuarial value in year $t + 1$. We censor actuarial value at zero for all consecutive coverage years where there is more than six months between the completion and initiation of a new coverage year. This rules out individuals who stockpile and postpone the onset of a new coverage period by more than six months. Median number of days from end of coverage year t to the start of a subsequent coverage year is capped at 365 days.

We continue to further explore the part of the gain from stockpiling that occurs because stockpiling reduces the number of coverage years initiated and, hence, the number of times consumers have to purchase under the deductible; the income effect. Because of the wedge in time between coverage years, a plan with coverage year initiation tied to episode-of-illness will lead to weakly fewer coverage years than a plan with calendar-based coverage year initiation—for *any* consumer. Consumers who never spend above the deductible are obviously indifferent regarding the plan types. Our formal analyses found some increase in the time to the next visit toward the end of the coverage year. To get a better sense of who actually benefits from the opportunity to initiate fewer coverage years, we depict the days between coverage years across the distribution of spending.[28] The last two columns of Table 9 show the median number of days from the end of one coverage year to the start

[28] Again, to address issues with the time horizon, we cap the median number of days from end of coverage year t to the start of a subsequent coverage year at 365 days.

of a subsequent coverage year, again by decile of total prescription drug spending in the coverage year. We see a clear negative relationship between the days until next coverage year and spending decile. Obviously, this is because one's spending percentile correlates with underlying health. What is striking, however, is that those who spend the most have in practice very short spells of time between coverage years, even in a system with clear stockpiling incentives. The median number of days until the start of a subsequent coverage year for the top spending decile, for example, is 17 days. Neither this group nor the 40–50% of consumers spending under the deductible have much practical gain from plan start anchored in episode-of-illness.

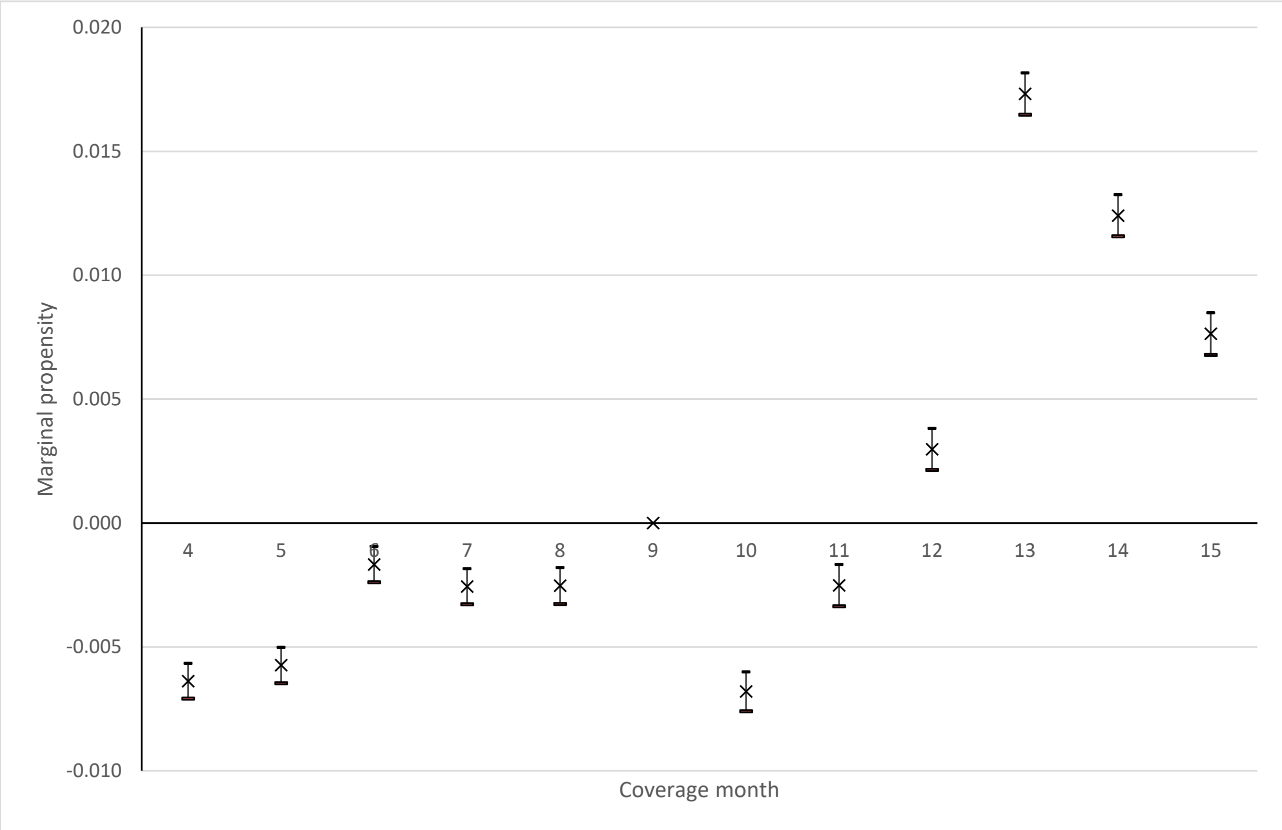
Short spells of time between coverage years might well be caused by acute conditions with non-deferrable treatment needs, forcing the onset of a subsequent coverage year. To investigate the extent to which this holds true, we apply our main difference-in-difference regression model from Section IV to estimate the probability of the first purchase in a coverage month including a drug-targeted acute disease.[29] We make two adjustments, however: we extend the model to include coverage months 13–15 and, thus, to avoid repeat observations, start the model in month 3. Results are shown in Figure 8. After the introduction of the nonlinear plan, coverage months 13–15 stand out; conditional upon starting one coverage year, subsequent coverage years that start soon after reset are significantly *more* likely to be initiated by the purchase of acute drugs. For example, consumers are 1.7 percentage points more likely to initiate coverage in month 13 with a purchase of an acute drug. In comparison, in 13% of all cases, coverage month 9 is initiated by the purchase of an acute drug.

[29] We define a drug (pharmacological class level; first four ATC digits) to be one targeted acute disease if fewer than 10% of consumers who buy this particular drug do so more than twice within a calendar year.

FIGURE 8

MARGINAL EFFECTS, PROPENSITY THAT FIRST PURCHASE

IN COVERAGE MONTH IS OF ACUTE TYPE



Notes: This figure shows estimated tendencies for individuals to initiate coverage months with the purchase of acute drugs by coverage month. Difference-in-difference estimation with individual-level FE as in Table 4 extended to include months 13–15. Sample years cover 1998–2014.

In summary, these analyses teach us that the monetary gains from stockpiling are actually relatively small for most consumers and that only part of the population (i.e., those spending over the deductible and those not too sick) stands to gain from retiming their purchases; and even then, unexpected acute disease may reduce the income effect associated with such strategic behavior. Stockpiling has also become less attractive over time as the cut-offs for the tiers have more than kept up with (pharmaceutical price) inflation. Given that we see a considerable share retime their purchases, all this in fact signals that individuals are highly sensitive to the reset of the coverage year. The question is the extent to which such intertemporal substitution affects traditional estimates of price sensitivity.

VIII. Implications for estimates of price sensitivity

We round off our analyses with an investigation of the importance of the transitory shifting of purchases across coverage years for price sensitivity estimates. Einav et al. (2015), for example, show how taking across-year substitution into account in their counterfactual policy simulation reduces the effect of filling the donut hole on utilization to one third. Similarly, Alpert (2016) finds that accounting for anticipatory effects in connection with the announcement halves the effect of the introduction of Medicare Part D on drug utilization.

A rich, growing literature addresses the price sensitivity of demand for health care—and especially the question of to which price consumers react. The set-up outlined in Brot-Goldberg et al. (forthcoming) is particularly relevant to our case. As described above, they study the shift from free health care to a non-linear, high deductible plan in a large, self-insured firm: ours is precisely also a set-up, although at the national level, with access to a pre-reform period with no within-coverage year price dynamics and where everyone is forced, via a universal policy, to switch to an environment where spot and shadow prices differ. We first implement a version of their main empirical strategy adopted to our setting and then investigate the consequences for the resulting estimates of leaving out the coverage months shown empirically to be influenced by intertemporal substitution. In this way, we decompose the overall elasticity estimates into variation coming from the early months of the coverage year and into variation coming from the last.

In order to track Brot-Goldberg et al. (forthcoming) as closely as possible, our estimation data set consists of a 10% random sample of all of the individuals who initiate a coverage year in 2000 or 2001, where coverage years initiated in 2000 correspond to their t_0 population and coverage years initiated in 2001 correspond to their t_1 population. In addition, our control year consists of individuals who initiate a (synthetic) coverage year in 1998, corresponding to their t_{-2} population. In this manner, we avoid problems caused by anticipatory spending that occur in the months leading up to the reform. An important difference between Brot-Goldberg et al. (forthcoming) and our set-up is, of course, that all individuals included in our estimations initiate a coverage year, and hence buy at least once, whereas in their context individuals who never purchase health care are also included.

Identification in Brot-Goldberg et al. (forthcoming) relies on simple cross-sectional assumptions on population health. The analysis assumes that conditional on health status at the beginning of a coverage month (s), health at the beginning of the coverage year (*H*), and background characteristics (*X*), pharmaceutical population needs in any coverage month post-reform are identical to those in any coverage month pre-reform. *s* is unobserved but the model assumes a one-to-one monotonic mapping between *s* and year-to-date spending (conditional on *H* and *X*), *S*. In line with our main analysis from above, we augment their conditioning set with individual fixed effects to account for any compositional effects over time. This also captures the existence of unobserved subsidies as described above.

The estimating equation is:

$$
\begin{aligned}
log\left(Y_{i,cm}+1\right) \\
&= \alpha_i + \left[\beta_e P^e_{i,cm} + \beta_s P^s_{i,cm} + \beta_L P^L_{i,cm}\right] + \left[\theta_e P^e_{i,cm} + \theta_s P^s_{i,cm} + \theta_L P^L_{i,cm}\right] I_{t_0 - t_1} \\
&+ \left[\delta_e P^e_{i,cm} + \delta_s P^s_{i,cm} + \delta_L P^L_{i,cm}\right] I_{t_1} + \gamma_H H_i + \gamma_X X_i + \gamma_{Y^l} \sum\nolimits_{l=1}^{2} log\left(Y_{i,t-1}+1\right) \\
&+ \sum_{cm \in CM} \gamma_{cm} I_{cm} + \sum_{m \in M} \gamma_m I_m + \sum_{t \in T} \gamma_t I_t + \epsilon_{i,cm}
\end{aligned}
$$

where *Y* is monthly incremental spending on health care, P^e is the shadow price (the expected end-of-year price), P^S is the spot price, and P^L is the prior year-end marginal price. Of the three prices, with a within-coverage year outlook, only the shadow price should matter for a fully rational and informed consumer. As mentioned above, however, studies have shown that spot prices could also matter; see Aron-Dine et al. (2015). We mirror Brot-Goldberg et al. (forthcoming) in their definitions of each of the prices.[30] *H* measures health status at the beginning of the coverage year and *X* background variables. The regression also controls for a function of lagged spending in addition to calendar (*m*) and coverage (*cm*) month as well as year (*t*) dummies. ε is an idiosyncratic error term and *i* indexes individuals.[31]

Table 10 shows selected results from this exercise with and without including coverage month 12. Importantly, despite the different context and the use of population-wide instead of firm-specific data,

[30] We use (synthetic) coverage years starting in 1997 (their t_{-3}) to impute expected end-of-year prices.
[31] Our results are robust to excluding the first month where everyone faces a spot price of one and to excluding consumers who only buy once in a coverage year.

our main conclusions regarding the spot price are surprisingly close to those from Brot-Goldberg et al. (forthcoming). They indicate that the spot price is important for purchasing decisions; currently spending under the deductible, for example, results in a 51 percentage points lower spending level compared to a situation where the price is 0.15. Interaction terms with 2001 are negative and, hence, indicate that consumers do not become less responsive to spot prices over time since the introduction of the nonlinear plan. Similarly, the estimates associated with the shadow price indicate that consumers spend slightly more when faced with a shadow price in one of the four highest quintiles compared to the lowest quintile. Interaction terms with 2001 are strongly negative and point to consumer learning.

Excluding coverage month 12 reduces the degree to which consumers seem to react to the spot price. The size of the reduction varies, but it is in the order of 14% in the case where consumers face a spot price under the deductible. Hence, while the main conclusions stand, ignoring intertemporal substitution across coverage years does inflate our estimates of spot-price sensitivity by a non-negligible amount. This even happens with the log-transformation of monthly spending that reduces the importance of very high levels due to stockpiling toward the end of the coverage year. Estimates associated with the shadow price are much less affected by the exclusion of month 12. This is plausible because there is no systematic relationship between coverage months and shadow prices.

TABLE 10

ESTIMATES OF PRICE SENSITIVITY

	Full	Excl. month 12
Spot price x treatment year		
1(deductible)	**-0.511**	**-0.442**
	(0.011)	(0.012)
1(deductible)x 2001	**-0.093**	**-0.116**
	(0.011)	(0.012)
0.5(coinsurance)	**-0.376**	**-0.310**
	(0.011)	(0.011)
0.5(coinsurance)x2001	**-0.052**	**-0.079**
	(0.011)	(0.011)
0.25(coinsurance)	**-0.215**	**-0.170**
	(0.009)	(0.010)
0.25(coinsurance)x2001	**-0.042**	**-0.059**
	(0.009)	(0.010)
OOP Max	**0.326**	**0.312**
	(0.046)	(0.052)
OOP Max x2001	0.057	0.022
	(0.041)	(0.047)
Shadow price x treatment year		
Quintile 2 - [0.193,0.437]	**-0.117**	**-0.136**
	(0.010)	(0.011)
Quintile 2 x 2001	**-0.075**	**-0.056**
	(0.010)	(0.011)
Quintile 3 - [0.437,0.833]	**-0.254**	**-0.273**
	(0.013)	(0.014)
Quintile 3 x 2001	**-0.240**	**-0.220**
	(0.013)	(0.014)
Quintile 4 - [0.833,0.957]	**-0.310**	**-0.330**
	(0.014)	(0.015)
Quintile 4 x 2001	**-0.338**	**-0.311**
	(0.014)	(0.015)
Quintile 5 - [0.957,1]	**-0.267**	**-0.277**
	(0.015)	(0.015)
Quintile 5 x 2001	**-0.371**	**-0.352**
	(0.015)	(0.015)
Individual level FE	X	X
# Observations	7073616	6484148
R^2	0.488	0.493

Note: 10% random sample of individuals making at least one purchase in the observation window. Standard errors clustered at individual level. Bold indicates significance at the 5% level. Excluded spot price category: coinsurance of 0.15. Excluded shadow price category: quintile 1 [0, 0.209]. Sample years cover 1998, 2000, and 2001.

IX. Conclusion

This paper investigates forward-looking behavior in the demand for prescription drugs. This type of behavior has important consequences for how to approach the estimation of price responsiveness. We exploit the introduction of a publicly financed, universal, non-linear insurance plan for prescription drugs in Denmark. The non-linear plan has two distinct features: 1) subsidies increase as expenditures accumulate, but the account is reset exactly 12 months after the first purchase and 2) the start of a subsequent coverage year is endogenous in the sense that it commences with the first purchase after reset. We discuss within the theoretical framework how these features incentivize intertemporal substitution in purchases; stockpiling effectively lowers out-of-pocket costs related to infra-marginal products (an income effect), because it minimizes the number of coverage years one needs to initiate. Additional savings may arise because stockpiling lowers the coinsurance rate on the marginal product (an effect on the price) without impacting the end-of-year price in the subsequent coverage year because of the endogenous onset.

We use population-wide registry-based Danish data to show that consumers react to the introduction of the non-linear plan by purchasing more immediately before the implementation of the new regime. We next describe behavior within the non-linear plan and formally analyze the consequences of the end-of-year reset for purchasing decisions while using a difference-in-difference strategy that relies on data from before and after the introduction of the non-linear plan. We show how consumers react to this future spot price increase by purchasing 20% more toward the end of the coverage year than they would otherwise have in a setting with a fixed coinsurance rate. We find considerable heterogeneity in the size of the response by individual-level characteristics, proxies for health status, and drug type. We find no evidence of associated adverse health effects or effects on health care utilization. We find some evidence of learning.

In our setting, it is both possible and legal to engage in intertemporal shifting of drug purchases without breaking the law. This is not true everywhere,[32] in which case we expect the amount of stockpiling to be smaller. Still, it might be difficult for authorities to detect that prescriptions are filled

[32] In the US, for example, only Florida, Louisiana, South Carolina, New York, and Missouri have a 34-day time limit for all prescription drugs (cf. CDC; 2015). Most of our estimates are well within this limit in terms of daily doses.

in December instead of January, let alone for them to prove that a slightly earlier purchase is due to stockpiling.

The welfare implications of the observed behavior are easily characterized, as consumers appear to be able to manage their pill consumption and to be suffering no loss of welfare in terms of short-run adverse health effects (which may or may not have been sufficiently internalized by the consumers choosing to stockpile). Assuming that consumers only solve a cost-minimization problem and incur no or only negligible storage costs, all that matters in terms of welfare is the trade-off between the lower average out-of-pocket cost per pill for those engaging in stockpiling versus the dead-weight loss of the extra tax that is required to finance this behavior. In cost-benefit terms, the saving accruing to the stockpilers is merely a transfer from one group in society (the average tax payer) to another (the needing pill consumer). The loss in economic efficiency from a small additional subsidy to the stockpilers is approximately equal to the behavioral (in the neoclassical sense) effects on government revenue. This can be non-trivial in a high tax regime such as the Danish (see Kleven and Kreiner, 2006).

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Appendix A. Additional tables and figures

TABLE A1

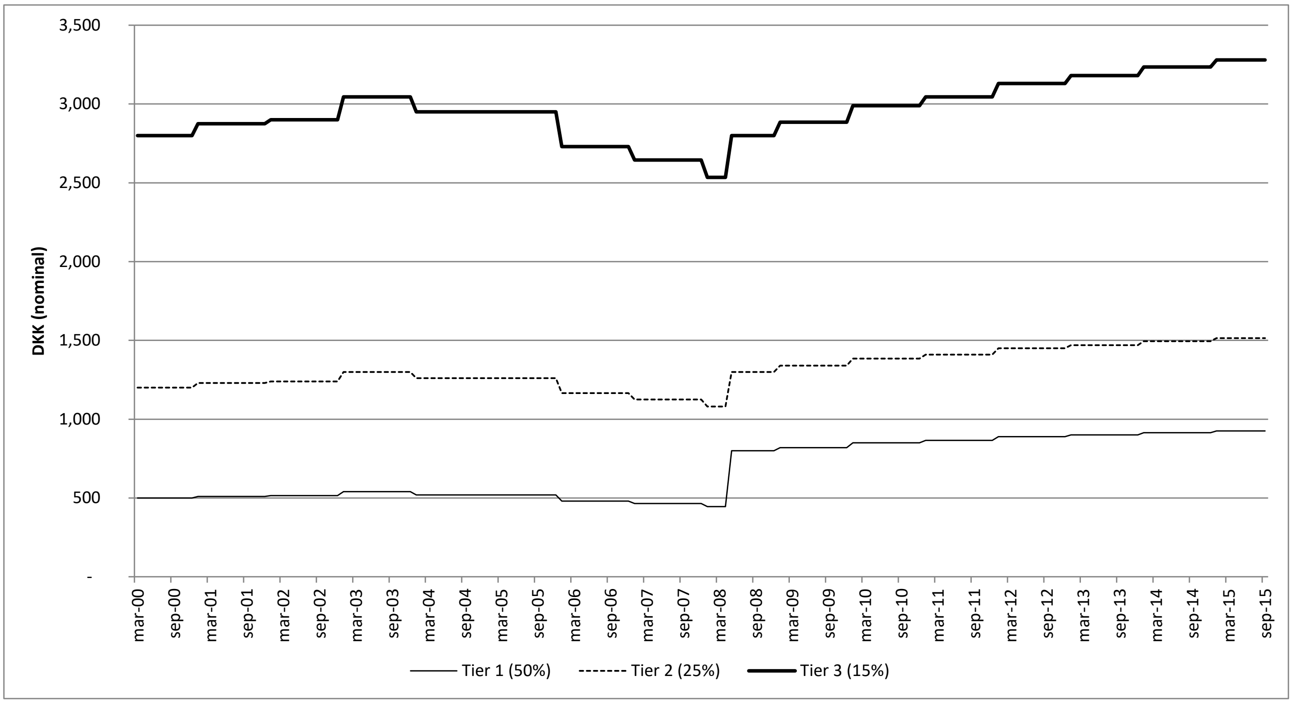
TOP TEN TYPES OF PURCHASED PHARMACEUTICALS WITHIN PRE-REFORM (1999) COINSURANCE RATES BASED ON Rx

Rank	ATC CODE	Number of *Rx*	% within rate	Drug type/name
Coinsurance rate of 50%				
1	J01CE02	873.380	7.5	Phenoxymethylpenicillin (penicillin V)
2	N02BE01	838.095	7.2	Acetaminophen (paracetamol)
3	M01AE01	646.716	5.6	Ibuprofen
4	B01AC06	637.625	5.5	Aspirin
5	N02AX02	531.026	4.6	Tramadol
6	A02BC01	415.019	3.6	Omeprazole (losec)
7	M01AB05	369.919	3.2	Diclofenac (Antiinflamatory/antirheumatic)
8	G03CA03	341.031	2.9	Estradiol (estrogen)
9	R05DA04	288.051	2.5	Codeine
10	J01EB02	226.495	2.0	Sulpha drugs
Total within rate			44.6	
Coinsurance rate of 25%				
1	C03CA01	582.544	4.0	Furosemide (High-ceiling diuretica)
2	C03AB01	547.779	3.8	Bendroflumethiazide
3	A12BA01	523.618	3.6	Potassium Chloride
4	R03AC02	382.680	2.7	Salbutamol
5	R03AC03	366.440	2.5	Terbutaline
6	R03BA02	346.035	2.4	Budesonide
7	N06AB04	340.337	2.4	Citalopram (anti-depressant)
8	C08CA01	329.272	2.3	Amlodipine
9	C01AA05	324.785	2.3	Digoxin
10	N02AG02	289.536	2.0	Ketobemidone
Total within rate			28.0	

Note: Own calculations based on full population of prescription drug claims in Denmark, 1999.

FIGURE A1

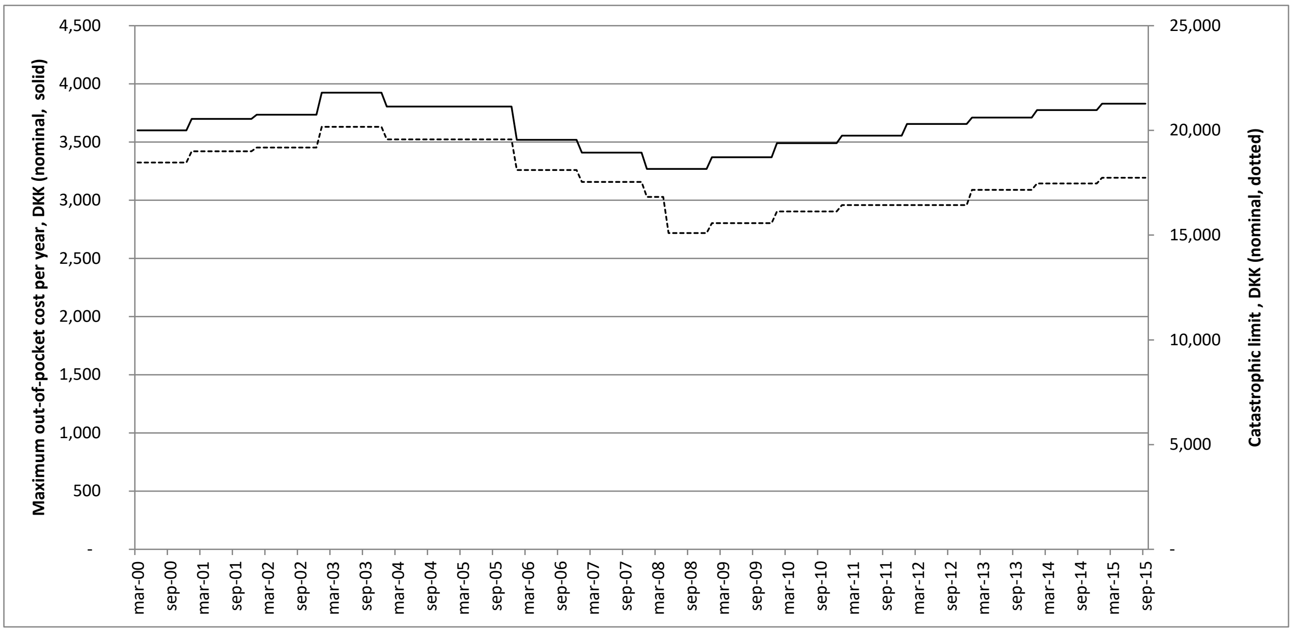
TIME SERIES VARIATION IN THE TIERS



Note: This figure shows how the three tiers of the universal non-linear insurance plan for prescription drugs changed over time.

FIGURE A2

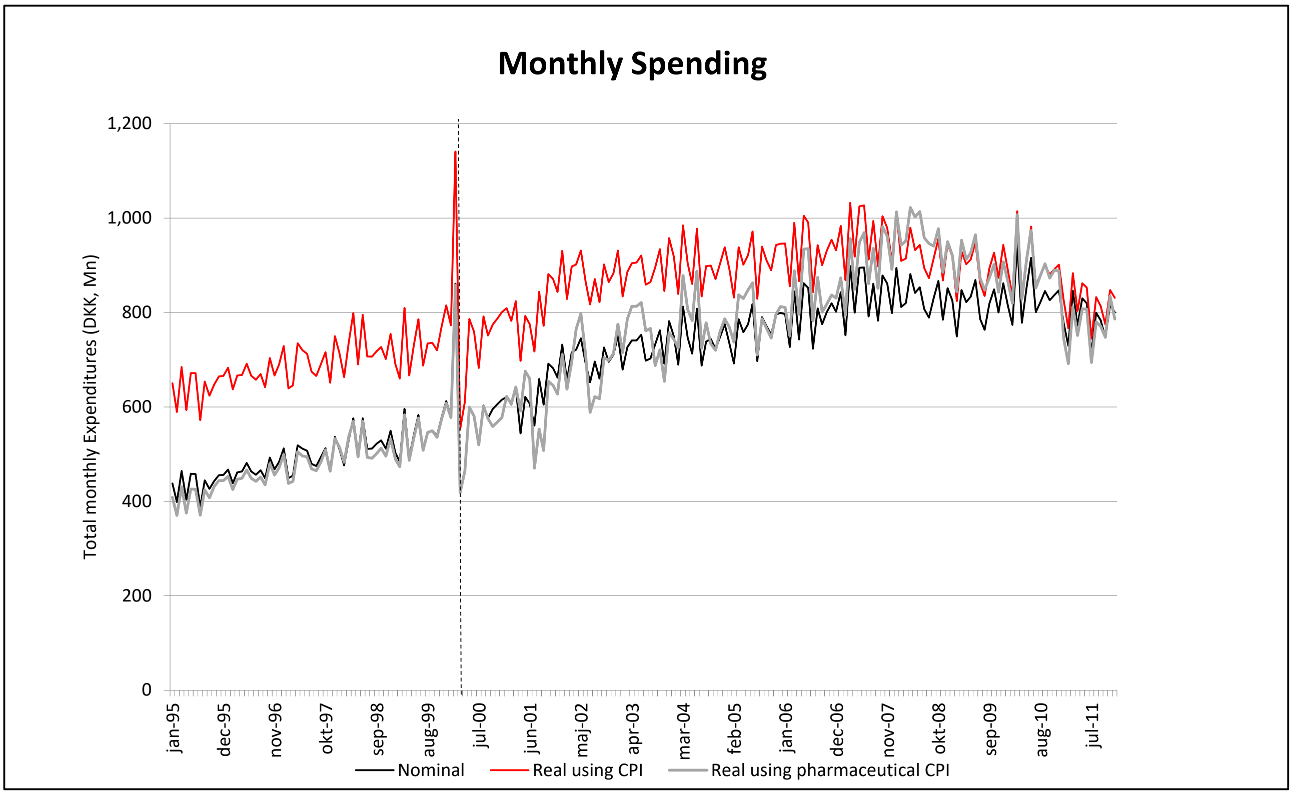
TIME SERIES VARIATION IN CATASTROPHIC LIMITS



Note: This figure shows how the maximum out-of-pocket costs and catastrophic limit associated with the universal non-linear insurance plan for prescription drugs changed over time.

FIGURE A3A

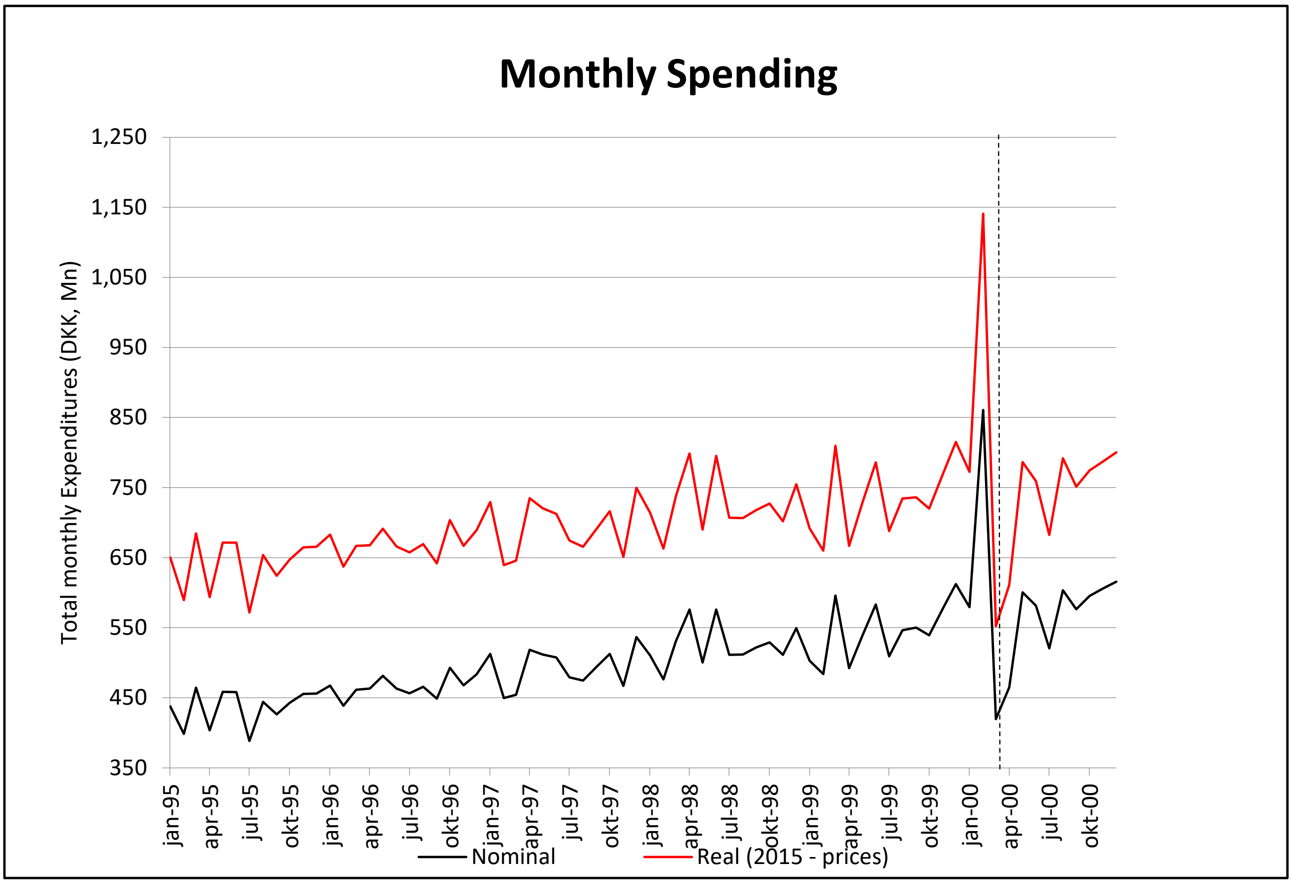
TRENDS IN CONSUMPTION, JANUARY 1995–DECEMBER 2011



Note: This figure shows trends in monthly expenditures over time. Real series adjusted for inflation using 2015 prices.

FIGURE A3B

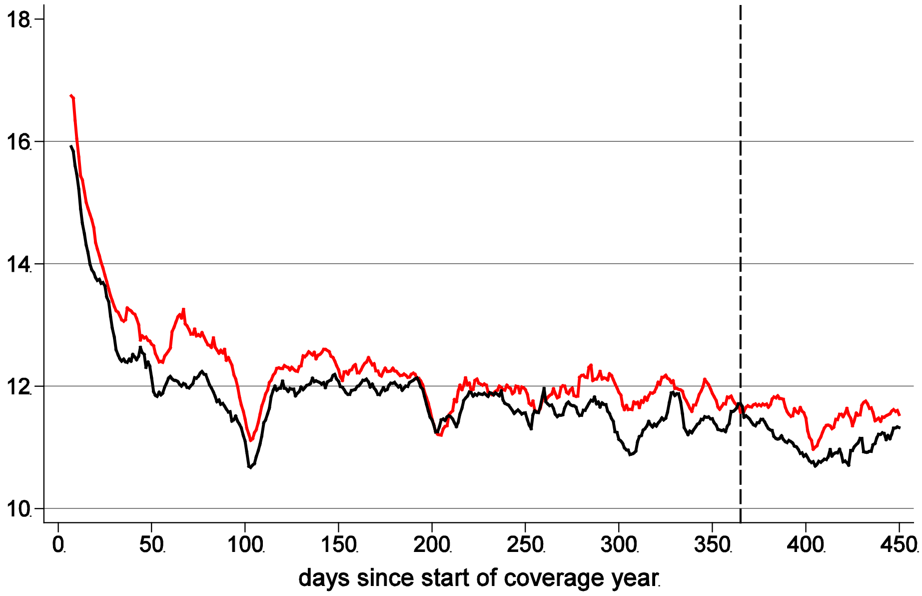
TRENDS IN CONSUMPTION, JANUARY 1995–DECEMBER 2000



Note: This figure shows trends in monthly expenditures over time.

FIGURE A4

SHELF PRICE—PRE- AND POST-REFORM

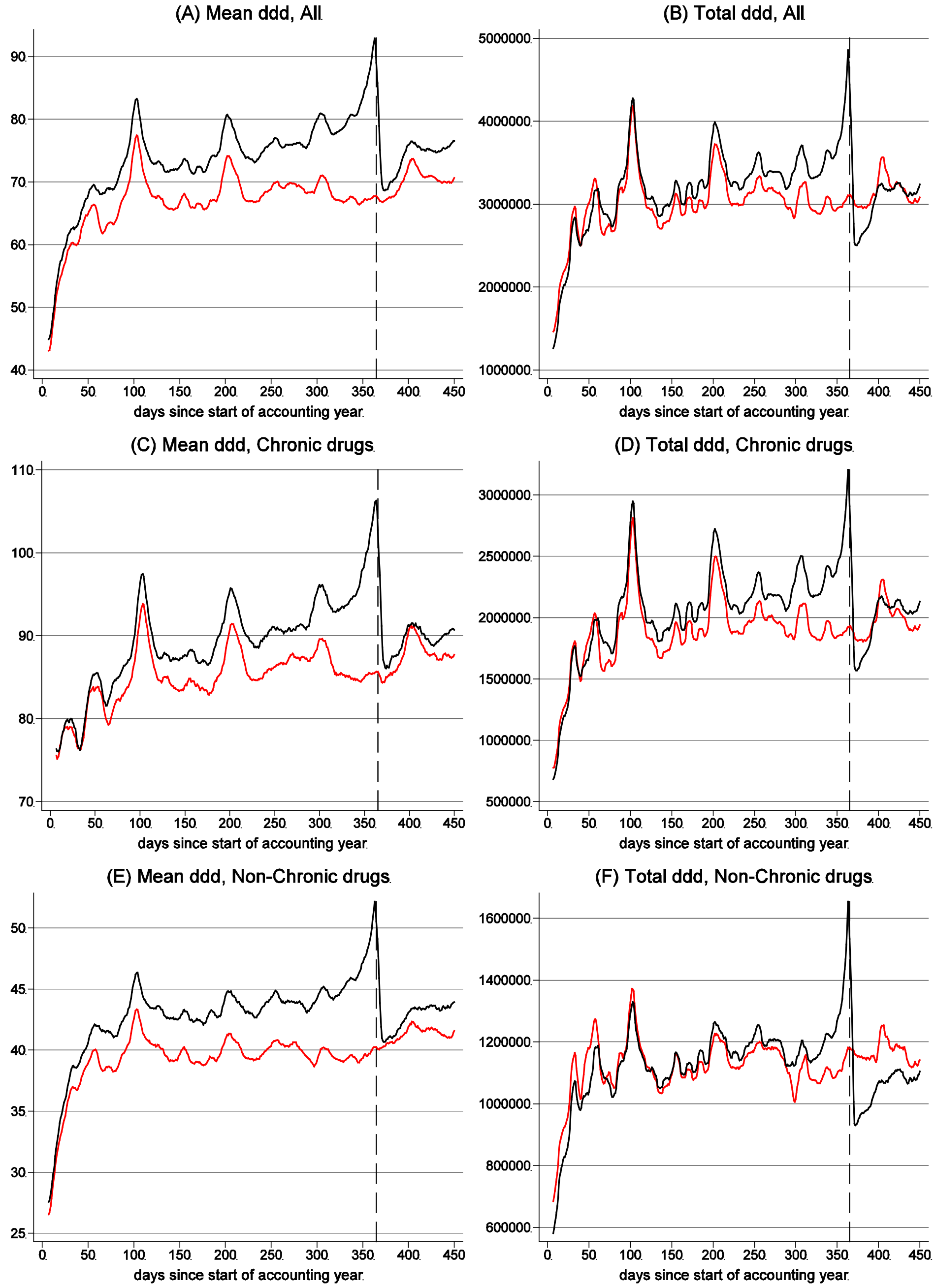


Notes: This figure presents evidence of individual behavioral responses to the end-of-year reset. Thick black line is post-reform, gray (red if read online) is synthetic pre-reform. The vertical dotted line separates days into current and next coverage year. Pre-reform data shows synthetic coverage years based on first purchases March–October 1998; post-reform data use first coverage year initiated March–October 2000. To smooth out day-of-week difference, an MA(7)-process is imposed on the daily data. First day in coverage year excluded from graph.

FIGURE A5

STOCKPILING EVIDENCE PRE- AND POST-REFORM:

CHRONIC AND NON-CHRONIC DRUGS

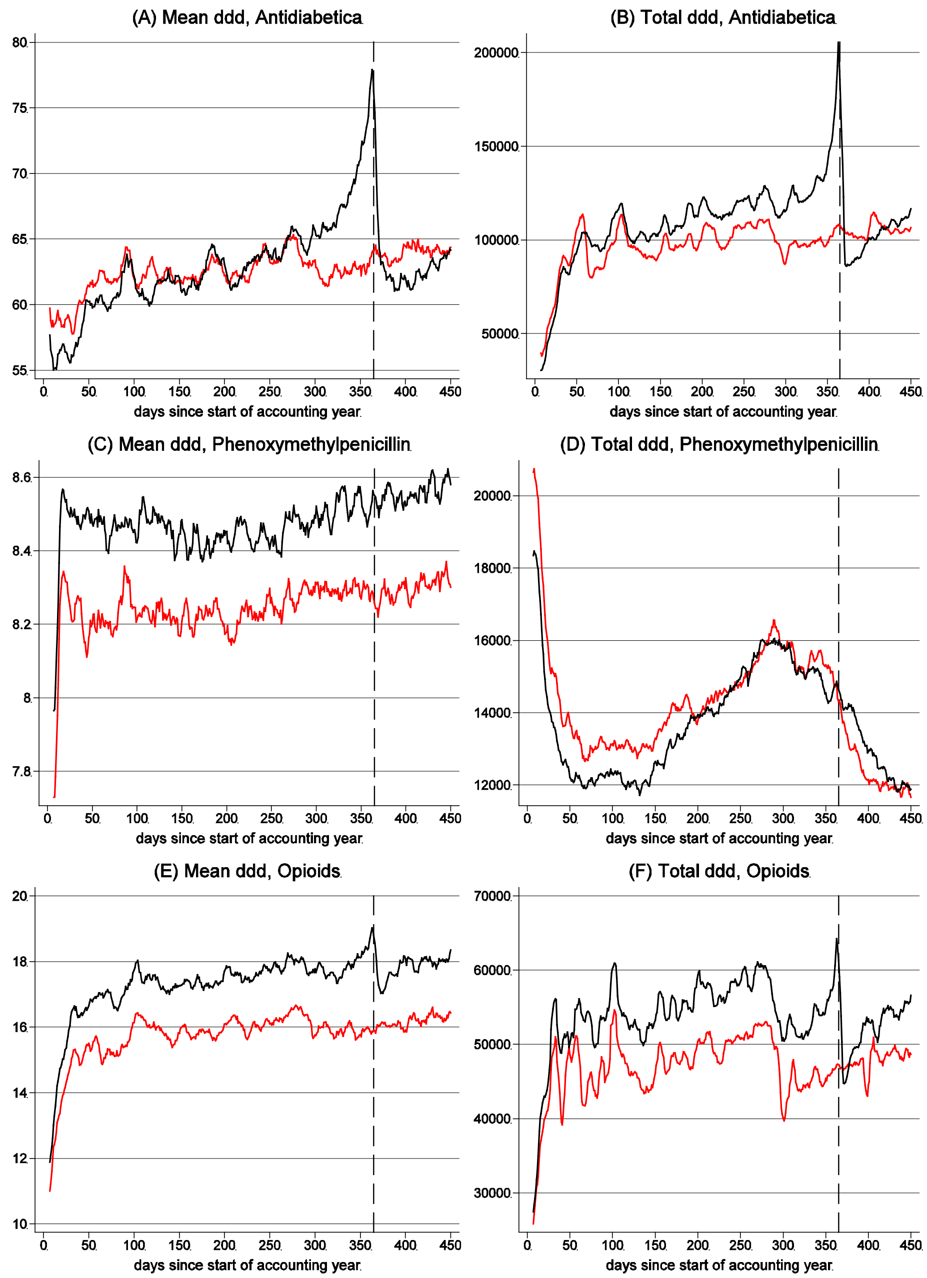


Notes: This figure presents evidence of individual behavioral responses to the end-of-year reset. Thick black line is post-reform, gray (red if read online) is synthetic pre-reform. The vertical dotted line separates days into current and next coverage year. Pre-reform data show synthetic coverage years based on first purchases March–October 1998; post-reform data use first coverage year initiated March–October 2000. To smooth out day-of-week difference, an MA(7)-process is imposed on the daily data. First day in coverage year excluded from graph.

FIGURE A6

STOCKPILING EVIDENCE PRE- AND POST-REFORM:

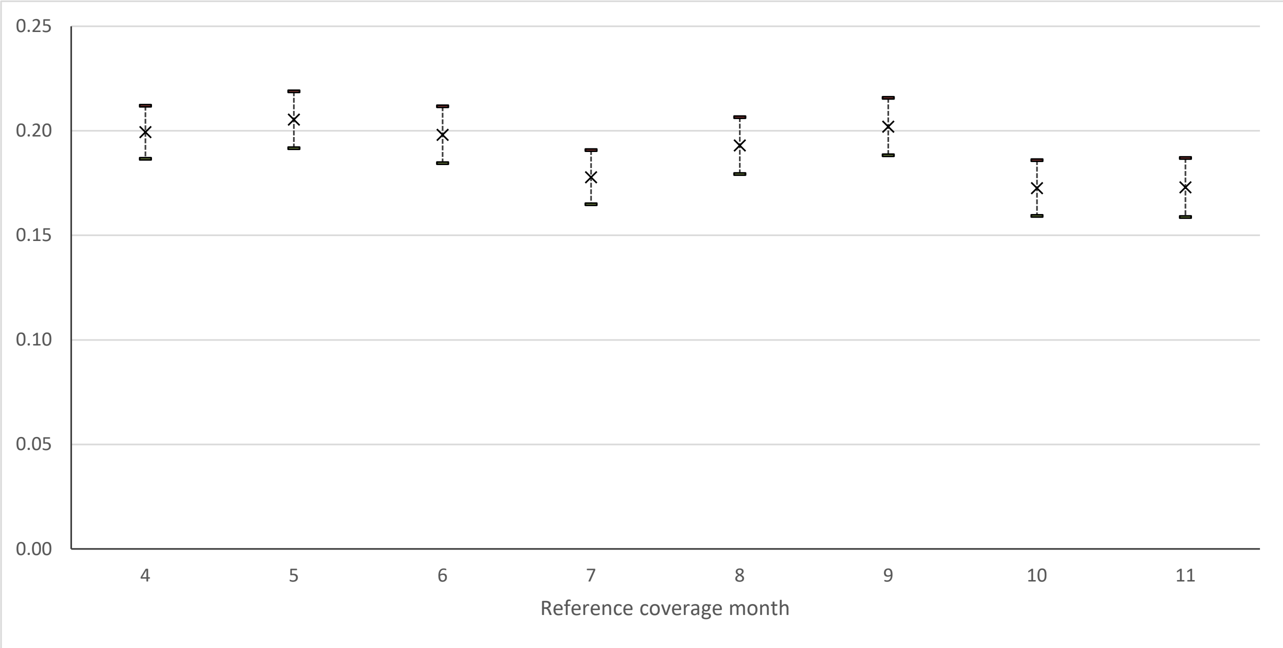
SPECIFIC TYPES OF DRUGS



Notes: This figure presents evidence of individual behavioral responses to the end-of-year reset. Thick black line is post-reform, gray (red if read online) is synthetic pre-reform. The vertical dotted line separates days into current and next coverage year. Pre-reform data show synthetic coverage years based on first purchases March–October 1998; post-reform data use first coverage year initiated March–October 2000. To smooth out day-of-week difference, an MA(7)-process is imposed on the daily data. Diabetes meds, ATC code: A10. Phenoxymethylpenicillin (penicillin V), ATC code: J01CE02. Opioids, ATC code: N02A. First day in coverage year excluded from graph.

FIGURE A7

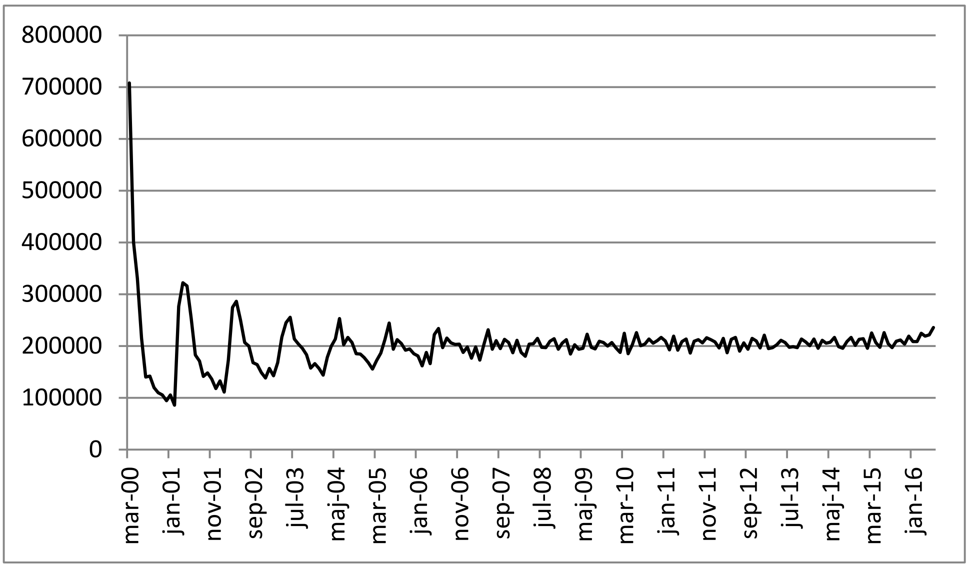
REACTION TO THE NON-LINEAR PLAN: MONTH 12 DIFFERENCE-IN-DIFFERENCE RESULTS WITH VARYING REFERENCE MONTHS



Notes: This figure shows estimated tendencies and 95% point-wise confidence bounds for individuals to spend more immediately prior to reset (version not conditional on purchase) by reference coverage month. Difference-in-difference estimation with individual-level FE as in Table 4 for groups of individuals who have initiated at least *x* coverage years with estimated behavior in coverage year *x*. Sample years cover 1998–2014.

FIGURE A8

COVERAGE YEAR INITIATION MONTH, OVER TIME



Notes: This figure shows the number of individuals with coverage year initiation in a given month after the introduction of the non-linear plan.

Appendix B. Classifying drugs as treating chronic diseases based on observed purchasing pattern

We follow Alpert (2016) and define a chronic drug based on whether the median consumer of the drug in question in a given year buys the drug more than twice. We measure the purchasing decision on a monthly basis; that is, we require at least three calendar months with an actual purchase for the median consumer before the drug is considered a drug treating a chronic condition. We classify drugs based on their anatomical therapeutic chemical (ATC) as defined by the WHO. This system divides drugs into several levels based on the organ or system upon which the drugs act (level 1; 14 groups), on their therapeutic subgroups (level 2; around 90 groups depending on year), on pharmacological subgroups (level 3; around 180), the chemical subgroup (level 4; 350 groups), and chemical substance (level 5; close to 900 different entries).

We treat drugs bought within the same pharmacological subgroup (level 3) as the same type but allow drugs within the same therapeutic subgroup (level 2) to belong to different categories. This means that magnesium compounds (A02AA) and aluminum compounds (A02AB) are treated as substitutes—they are both antacids (A02A)—but classified differently than pantoprazole (A02BC02), a proton pump inhibitor (A02BC) used to treat peptic ulcers and gastro-esophageal reflux diseases, (A02B) even though all three drug (compounds) are used to treat acid-related disorders.

Appendix C. Predicting pharmaceutical spending

To predict pharmaceutical spending, we follow the approach outlined in Handel (2013). We construct a predictive model based on population-wide panel data informative about pharmaceutical spending, diagnoses, and cost information.

In the analyses of reactions to the introduction of the reform, we first regress pharmaceutical spending in calendar year t on a dummy for gender in addition to $t-1$ age, age squared, number of visits to own GP, sum of fee-for-services paid to GP, total spending on prescription drugs and total expenditures squared, indicators for type of prescription drugs purchased (ATC code level 3; 88 categories), and hospital diagnosis indicators (ICD-10 code level 2; 215 categories). The resulting models explain between 75–80% of the variation in spending. We then use the estimated model to predict individual-level spending in calendar year $t + 1$. Thus, to classify consumers in terms of their health index, we regress spending in 1999 on 1998 covariates and use this model for out-of-sample predictions for

2000 spending using 1999 covariates. To do so meaningfully, we assume that there is no strategic reaction to the introduction of the reform already in the last months of 1999. This is in line with the descriptive evidence in Figure A3.

We proceed similarly in the analysis of reactions to coverage reset, except that we anchor spending outcome in coverage years instead of calendar years. Explanatory variables are measured in the 365 days preceding the initiation of the coverage year in question.

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