Essays in Behavioral Health Economics

by

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Abstract

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This dissertation is composed of two chapters. Each chapter presents a study testing a theory from behavioral economics in a health economics setting using field data.

The first chapter studies the role of present bias in the choice of health insurance. I analyze the consequences of a policy change that removes deadlines for enrollment in high-quality (5-star) Medicare drug coverage plans (Part D), while maintaining existing deadlines for enrollment in all other plans. Although the goals of the policy were to increase enrollment in 5-star plans and to provide incentives for insurers to improve quality, the removal of deadlines might lead to the opposite. First, rational beneficiaries might wait to enroll in 5-star plans only when a negative health event occurs, which would both decrease enrollment and increase adverse selection. Second, without deadlines, present-biased beneficiaries might procrastinate, which would also lead to a drop in enrollment, driven by an overall increase in inertia. I develop a model to examine these different hypotheses and test its predictions using Medicare administrative micro data for the period of 2009-2012. I employ a difference-in-differences design within a differentiated-product discrete-choice demand framework. My identification strategy takes advantage of the fact that the policy did not actually change enrollment rules everywhere in the United States, as most counties were not within the coverage area of a 5-star provider in 2012, the year the policy was implemented. I have three main findings. First, the policy backfires: it decreases enrollment in the Part D program by 2.55pp from a baseline of 51.76%, and decreases average market share of 5-star plans by 1.37pp from a baseline of 7.78%. Second, the policy does not seem to impact adverse selection, suggesting the rational model might not fully account for the results. Third, the removal of deadlines leads to a drop in the probability that a previously enrolled beneficiary switches plans of 3.18pp (baseline 9.08%), suggesting that at least some Medicare beneficiaries are present-biased.

The second chapter studies role of projection bias in mental health treatment decisions. Evidence from psychology suggests that on a bad-weather day, individuals may feel more depressed than usual. If people are not fully able to account for the effect of transient weather, they may take systematically biased treatment decisions. I derive a model of a

person considering treatment for depression and show that when projection bias is present, transient weather might influence choice. I use detailed administrative medical records from the MarketScan database and daily county-level meteorological data from the National Climatic Data Center. My period of analysis is 01/01/2003 through 12/31/2004. My main analysis focuses on patient behavior during a small interval of time after they have been seen by a physician. I look at how weather influences antidepressant filling decision within patient and only include appointments that involved a major diagnosis of a mental disease or disorder. I find that a one standard deviation increase in the amount of cloud coverage (2.73 oktas) leads to a 0.063 percentage point increase in the probability that a patient fills an antidepressant prescription on appointment day. That is a 1.04% increase from the 6.07% baseline. I also find effects associated with snow, rain, and temperature. All effects fade with time and are not significant within seven days of the appointment. Most of the impact of cloud coverage on antidepressant filling is due to an increase on the number of new prescriptions, not an increase in refills. Virtually all the effect happens at the pharmacy, not via mail order. Most regions have similar coefficients associated with cloud coverage, with stronger results in the Northeast and Upper Midwest. Finally, most of the impact happens during Winter.

To Emmanuel Large.

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Chapter 1

The Cost of Removing Deadlines: Evidence from Medicare Part D

1.1 Introduction

Recent health insurance policy innovations—including Part D of Medicare and the Affordable Care Act—are grounded on the notion that consumer choice can be a powerful force for lowering costs and improving efficiency (see e.g., Dayaratna, 2013). Nevertheless, the complexity of the health care system in particular, and insurance markets in general, places a substantial burden on consumers to choose wisely among alternative plans.[1] In the case of Medicare Part D, an opt-in program available to Medicare beneficiaries, participants may choose among alternative prescription drug plans (PDP's) offering widely different pricing regimes for different prescription drugs. A number of recent studies have found that many Part D participants' plan choices are sub-optimal given their actual drug use patterns (Heiss et al. [2010], Abaluck and Gruber [2011, 2014], and Heiss et al. [2013]).

In 2007, the Centers for Medicare and Medicaid Services (CMS) introduced an annual 5-star rating system designed to help Part D participants to choose among the PDP's available in their area. The stars are awarded on the basis of multiple factors, including surveys of plan participants about the quality of customer services, call center performance, member complaints, and accuracy of information on drug pricing. A second major step was taken in 2012, when CMS introduced a new policy allowing Medicare beneficiaries to enroll in 5-star plans **at any time**, rather than having to wait until the open enrollment period in the late fall. The intention of the new policy, as stated by CMS officials, was to "get beneficiaries into 5-star plans" (Moeller, 2011) and "give plans greater incentive to achieve 5-star status" (Crochunis, 2010). Despite these intentions, in 2014 there was no PDP with a 5-star rating, and only 5 percent of Part D participants were enrolled in plans rated with four or more stars (Hoadley et al, 2014). In 2015, the 5-star classifitation was again granted to some PDP's.

[1] See Einov and Finkelstein (2011) for a recent review of selection in insurance markets.

In this paper, I use a combination of aggregated county-level information and individual-level enrollment records to evaluate the effects of the new open enrollment policy for 5-star Part D plans. While the intention of CMS administrators was to nudge participants toward choosing a 5-star plan, careful consideration of the choice behavior by Medicare beneficiaries suggests that the policy could have easily led to a **reduction** in enrollment in 5-star plans and even a **reduction** in overall enrollment in the Part D program, albeit existing incentives for participation.[2] Making it possible to join a 5-star plan at any time in the year could induce healthy Medicare participants with no major prescriptions to go without Part D coverage and only enroll if and when their health deteriorates—an adverse selection effect that would be expected under fully rational choice behavior. Likewise, eliminating the enrollment window for 5-star plans eliminates the deadline for active choice—an effect that could lead present-biased Medicare beneficiaries to procrastinate joining Part D or switching plans, resulting in lower overall enrollment in the preferred plans. Arguably the only situation where eliminating the enrollment window for 5-star plans could actually increase enrollment in these plans is the case where beneficiaries randomly forget to enroll.

To test the predictions of the different models, I combine Medicare enrollment data from 2009 to 2012 with detailed information on the benefits, costs, and coverage areas for all Part D plans available during these years. My identification strategy exploits the time-series variation on the star rating of Part D insurers. I take advantage of the fact that not all counties in the United States were within the coverage area of an insurer that was rated 5 star in 2012—when the deadlines for enrollment in those plans were removed. This feature sets up a straightforward difference-in-differences design that compares Part D enrollment choices of Medicare participants in counties with and without a 5-star plan available in 2012.

Looking first at overall Part D enrollment, I find that the availability of a 5-star plan was associated with a 4.92% drop in overall participation in PDP's, from a baseline of 51.76%. For new Medicare beneficiaries (i.e., those who enter Medicare for the first time in the current year), I find a 15.73% decrease in participation by the initial deadline for enrollment in Part D.[3] For continuing beneficiaries (i.e., those who were enrolled in Medicare in the previous year), I find a 3.63% drop in participation during the fall open enrollment period. The difference in effect magnitudes between new and continuing enrollees can be attributed to the high inertia observed among beneficiaries previously enrolled in a plan, and to an alleged higher awareness of the policy among new beneficiaries. In fact, the drop in enrollment decreases by age group, and is not statistically significant for those over 80 years old.

To analyze the effects of the new policy on the choice of a particular PDP, I estimate a version of the Berry (1994) differentiated-product discrete-choice demand model, incorporating the absence of deadlines for enrollment as a time-varying plan characteristic. I find a negative impact of the policy on the market share of 5-star plans. By the original deadline, average market share of 5-star plans falls 1.37 percentage point, from baseline 7.78%.

[2]Upon joining Part D, beneficiaries who lacked drug coverage for over two months might have monthly premiums increased by $0.32 per month of non-enrollment.

[3]End of third month after becoming eligible for Medicare.

I conduct a series of robustness checks to verify these results. First, I assess how enrollment varies with the maximum-star-rating of any insurer in the county in the periods before and after the new policy. There is a drop in enrollment post-policy change in counties within the coverage area of a 5-star insurer, but not in counties in which the highest-rated insurer received a 4.5 or 4.0 classification. This pattern indicates that the results are not due to factors common to all counties with highly-rated insurers. Analogously, an analysis of the effect of star rating on plan enrollment on the pre- versus post-policy change period, within counties with a 5-star insurer, corroborates the market share results.

Taken together my findings on overall Part D enrollment and enrollment in 5-star programs suggests that the policy of allowing open enrollment for 5-star PDP's backfired. This failure could be attributed to an adverse selection effect—arising because healthier Medicare participants choose not to enroll in Part D when a 5-star plan can be joined at any time in the year—or a present bias effect—arising because Medicare participants fail to enroll once the deadline for making a choice is removed.

The adverse selection channel should have only affected relatively healthy beneficiaries who decide not to enroll or who opt out of Part D, and 5-star plans in particular. To test this explanation, I use costs of the services provided to beneficiaries under Parts A and B of Medicare as a proxy for their health status. The increase in adverse selection arising from the policy change should lead to an increase in the average cost incurred by enrollees of 5-star plans. Using this identification strategy, I fail to reject the null-hypothesis of no impact of the policy change on adverse selection into 5-star plans. The same is true for both new and continuing enrollees.

As a second check, I use end-of-the-previous-year chronic conditions indicators. I assess how the drop in enrollment caused by the policy varies depending on common illnesses such as heart failure, diabetes, and hypertension. I focus on the behavior of continuing enrollees—for whom the data is available—by the original December 7th deadline. For each condition, I compare the responses to the policy of the group with the illness to that of the group without it. Again, I find no evidence of an adverse selection effect. For most conditions, the responses of the healthy and of the ill are of similar magnitude.

To test the present bias explanation, I measure the degree of inertia exhibited by the PDP choices of Part D participants in consecutive years. If participants are present biased, the removal of the deadline to switch into a 5-star plan would be expected to lead to a lower probability of switching plans. Consistent with this prediction, I find that the policy change decreases the probability that a current enrollee switches plans by the original December 7th deadline by 3.18 percentage points, down from the average 9.08% switching probability. I consider the increased inertia caused by the policy prima facie evidence of present bias.

The remaining of the paper is organized as follows. Section 1.1 discusses contributions to existing literature. Section 1.2 presents background information on Medicare, the Part D drug coverage program, the original deadlines for enrollment, and the policy change that removed the deadlines for enrollment in 5-star plans. Section 1.3 introduces the model.

Section 2.3 describes the administrative Medicare data. Section 1.5 discusses the impact of the policy on take-up of the program and on plan market shares. The impact of the policy on adverse selection and inertia are discussed in sections 1.6 and 1.7, respectively. Section 2.7 concludes.

Contributions and Related Literature

This paper contributes to the understanding of how deadlines impact enrollment and cost of coverage in the Medicare Part D market, with lessons readily applicable to the broader Medicare, a program that provides health insurance to approximately 50 million beneficiaries, and accounts for 14.22% of the federal government's budget, or $498 billion in 2013.

This paper also contributes to the debate surrounding behavioral-inspired policymaking. The governments of the United Kingdom and of the United States, among others, have recently consulted with behavioral insights teams (nicknamed 'nudge units') in the design of public policies that incorporate insights from behavioral economics and the behavioral sciences. This movement sparked a strong reaction among some circles in academia and in the public debate. According to a recent article in the Economist (2014), behavioral-inspired policies might backfire because "bureaucrats and their bosses are as full of blind spots and weak spots as any of the people they govern." But deviations from strict rationality were already considered in policy long before the establishment of nudge units. This paper provides an example of an 'old-school' policy inspired on a non-rational hypothesis, forgetting, that could in principle backfire because people are either more rational than expected, irrational in an unanticipated way, or both.

This paper relates to Handel (2014), who finds that policies aimed at decreasing inertia and nudging consumers to better health insurance choices might lead to welfare losses due to an increase in adverse selection. More generally, this paper contributes to a growing literature on the failure of consumer optimization in insurance markets. Abaluck and Gruber (2014, 2011) finds that a majority of participants in Medicare Part D are enrolled in a dominated plan, yet fail to switch to plans with better risk protection at a lower cost. Ericson (forthcoming) reports that older Part D plans have higher premiums, consistently with the predictions of a model in which sophisticated insurers and present-biased beneficiaries. Bhargava, Loewenstein and Sydnor (2014) finds that the majority of the employees of a Fortune 100 American company in the health-care industry choose a dominated health plan. Loewenstein et al. (2013) finds that Americans have a limited understanding of how traditional health insurance plans work. Handel and Kolstad (2014) provides evidence on the role of information frictions and hassle costs in health insurance choice. Other papers in this literature include the work of Taylor, Cebul, Rebitzer and Votruba (2011) on search cost.

This paper also relates to the behavioral literature on present bias. There is a considerable amount of evidence to support that deadlines help individuals overcome self-control problems. Ariely and Wertenbroch (2002) find a positive impact of deadline on student performance. Additionally, existing evidence supports the notion that individuals might be at least partially naive with respect to future willingness to delay immediate gratification, and may therefore benefit from the use of commitment devices such as deadlines. DellaVigna and Malmendier (2006) and Ausbel (1999) find that individuals underestimate future present bias. A related set of literature, including Madrian and Shea (2001), Choi et al. (2004), and Cronqvist and Thaler (2004), highlights the sizable impact of defaults in behavior, even in the presence of small switching costs.

1.2 Background

Medicare is a federal health insurance program in the United States that provides health insurance for Americans aged 65 and older, younger people with disabilities, and people with conditions such as end stage renal disease or amyotrophic lateral sclerosis. The default coverage, known as Original Medicare, is a public fee-for-service hospital (Medicare Part A) and medical (Medicare Part B) insurance.[4] In 2012, Medicare provided health insurance to 50.8 million beneficiaries. The program is administered by the Centers for Medicare and Medicaid Services (CMS), an agency of the Department of Health and Human Services. Benefits of the program are controlled by the U.S. Congress. In 2013, spending on Medicare accounted for 14.22% of the federal budget, or $498 billion. In 2012, the program was responsible for 20% of the total national health spending, 27% of spending on hospital care, and 23% of spending on physician services (CMS, 2014).

Private Medicare Plans

The federal government also operates a prescription drug benefit (Medicare Part D) that subsidizes the costs of prescription drug insurance for Medicare beneficiaries. Part D was enacted as part of the Medicare Modernization Act of 2003 and went into effect on January 1, 2006. Beneficiaries enrolled in Original Medicare can enroll in a private standalone prescription drug plan (PDP). Alternatively, beneficiaries may leave Original Medicare and enroll in a private health insurance plan (Medicare Part C), which combines hospital and medical insurance. Most Part C plans include prescription drug coverage (MA-PD).

Medicare beneficiaries have several options. In the PDP market alone, there were an average of thirty one options from which to choose in 2012. The number of PDP's available varies yearly and differs across counties in the United States. In 2012, 31.8 million beneficiaries received Medicare Part D benefits—19.9 million in PDP's, and 11.9 million via a MA-PD plan.

[4]Part A covers hospital, skilled nursing facility, home health, and hospice services; Part B covers doctors, outpatient services, preventive services, lab tests, ambulance services, and medical equipment and supplies. Medicare Part B is an opt-in program in Puerto Rico.

Part D Drug Coverage Plans Medicare drug plans vary in terms of premiums, deductibles, coinsurance, and drug coverage, among others characteristics. All plans must, at a minimum, be actuarially equivalent to a defined standard benefit. In 2012, the standard benefit had a deductible of $320, and required 25% coinsurance up to the initial coverage limit of $2,840 (full retail cost of prescriptions). At that point, a beneficiary would enter the "donut hole," and pay full cost for prescription drugs until total out-of-pocket expenses reached $4,700, at which point catastrophic coverage begins. Once catastrophic coverage is triggered, the beneficiary pays the greater of 5% coinsurance, or a copay of $2.65 for generic drugs and $6.60 for brand-named drugs.

5-star Rating System To promote informed choice, CMS annually evaluates the quality of the services provided by private insurers using a 5-star rating system. Appendix A discusses the data sources and specific variables used to evaluate Medicare Part D insurers. The five-star classification was first announced in October 2007, with ratings valid for the 2008 calendar year. CMS is instructed by Social Security Administration to broadly disseminate information on Medicare options. When a beneficiary has the option to make changes in coverage, she receives notice from CMS with a list of plan options and their characteristics (Social Security Act 1804, 1851[d]). The same information is available online. Figure 1.1 presents the results of a search for plans available in Minneapolis, MN on the official Medicare website.

Deadlines for Enrollment Typically, beneficiaries can only enroll in or change from one Part D plan to another at specific times during the year. New beneficiaries can enroll during the seven-month period that ends 3 months after the month they turn 65 and become eligible for Medicare. Current beneficiaries can enroll, drop, or switch plans every year during the annual Open Enrollment Period, which currently ends on December 7th. The new choices are implemented on January 1. There are several exceptions to these enrollment rules, which I briefly discuss on Section 1.4. Beneficiaries who lack drug coverage for an extended period of time might pay a late penalty fee at enrollment. The fee amount is added to the Part D premium, and is incurred if there is a period of 63 or more days in a row when a beneficiary lacks Part D or other creditable prescription drug coverage. In 2012, the fee was $0.32 for un-enrolled month.

Removal of Deadlines for Enrollment in 5-star Plans

In 2012, CMS removed all deadlines for enrollment in plans offered by insurers with a 5-star rating. The policy change allows beneficiaries to enroll in or switch to a 5-star plan at any time, while maintaining the original deadlines for enrollment in all other plans. Figure 1.2 depicts the pre- and post-policy change deadlines for enrollment in Part D plans for new and continuing Medicare beneficiaries.

Intended Consequences The intended consequence of the policy, as stated by CMS officials, was to increase enrollment in 5-star plans, thus providing incentives for plans to improve the quality of their service.

> "We want to get beneficiaries into 5-star plans." Former Medicare chief J. Blum to U.S. News (Moeller, 2011)
>
> "..give plans greater incentive to achieve 5-star status." Medicare Enrollment Coordination Dir. M. Crochunis (Crochunis, 2010)

The policy can be regarded as an attempt to nudge beneficiaries to enroll in 5-star plans. The presumed model of behavior underlying the removal of the deadlines for enrollment in 5-star plans incorporates the hypothesis that beneficiaries may randomly forget to enroll, which I call Random Forgetting. Under Random Forgetting, the resulting change in behavior is consistent with the goals stated by the policymaker: there is no impact on enrollment by the original deadline and enrollment in 5-star plans increases afterwards. Figure 1.3a summarizes the intended consequences of the policy.

Informing Beneficiaries About the Policy Figure 1.1 illustrates the content and framing of the information about the policy that is available to beneficiaries. In the document that CMS mails to beneficiaries whenever they can make changes in enrollment, and on the web, a golden star is displayed alongside plans offered by insurers rated 5 star, reminding beneficiaries that "if a plan has a 5-star rating, people with Medicare can switch into that plan at any time during the year, even if it's not during an enrollment period." As Figure 1.1 shows, the explanation of what the golden star means in terms of enrollment past the original deadline is one of the most conspicuous elements on the Medicare Plan Finder website.

1.3 Theoretical Framework

I model the joint participation decision and plan choice of a beneficiary in the PDP market and derive testable predictions about the impact of the policy change on enrollment behavior. Section 1.3 introduces a fully-rational discrete-choice framework, which I label Option Value model given its underlying mechanism in this particular setting. I show that, as long as beneficiaries face health risk, the policy change leads to a drop in enrollment in 5-star plans by the original deadline. In Section 1.3, I expand the model by allowing beneficiaries to display naive present bias as in O'Donoghue and Rabin (1999). Under present bias, the policy increases inertia by the original deadline, and leads to a decrease in enrollment in 5-star plans even if health is (perceived to be) immutable.

In Section 1.3, I discuss abridged versions of the model with the goal of illustrating underlying mechanisms in the simplest way possible. I derive predictions about the behavior of an un-enrolled beneficiary. Section 1.3 discusses a version of the Option Value model with three plan options (5 star, non-5 star, unenrollment) and two health states (healthy, sick).

As the average 5-star plan has a larger premium and a lower deductibles, I assume they yield a higher payoff for the sick. In that model, the decrease in enrollment in 5-star plans by the original deadline is driven by changes in the behavior of the healthy, leading to an increase in adverse selection. Section 1.3 also discusses a simple model with present bias and no health risk. Finally, Section 1.3b discusses a simple version of a model in which beneficiaries might forget to enroll—the model the policymaker alledgedly considered at the time the policy was designed.

Set-up

A beneficiary decides whether to participate in Medicare Part D and in which plan to enroll. The beneficiary can switch plans at time $t = 0$, the original deadline. For simplicity, I assume that, pre-policy change, that is the only time in which she can switch plans. At time $t = 1$, coverage in the chosen plan starts. The length of a time period is a month, and the beneficiary lives forever. Switching plans costs $c > 0$.

The enrollment decision is taken under uncertainty with regards to future health. At each time t, the beneficiary is characterized by the pair (h_t, p_t), where $h_t \in \mathrm{H}$ is her health state, and $p_t \in \{p^o, p^1, p^5\}$ is the plan in which she is enrolled.[5] Let $\pi_h(h) = \mathrm{P}\left[h_{t+1} = h | h_t\right]$ denote the monthly transition probability between any two health states. Let p^5 be a 5-star plan, p^1 a non-5 star plan, and p^o the outside option (unenrollment). Denote the instantaneous payoff from plan enrollment by $u^t(h_t, p_t)$.[6] The actual time-t discounted value associated with (indefinite) enrollment in a plan is defined as

$$U^t(h_t, p_t) = \sum_{\tau \geq t} \delta^{\tau - t} u^\tau(h_\tau, p_t). \tag{1.1}$$

The policy change allows beneficiaries to enroll in p^5 at any time. Let $V^t(h_t, p_t)$ be the post-policy change continuation value associated with enrollment in a plan. I abstract the late-penalty fee from the analysis. At $t \geq 1$, we have

$$V^t(h_t, p_t) = u^t(h_t, p_t) + \max\left\{\delta \mathrm{E}\left[V^{t+1}(h_{t+1}, p_t)|h_t\right], -c + \delta \mathrm{E}\left[U^{t+1}(h_{t+1}, p^5)|h_t\right]\right\}. \tag{1.2}$$

The possibility of switching to the 5-star plan adds an option value to the payoff expected from enrollment in all plans that are not 5-star. Note that $V^t\left(h_t, p^5\right) = U^t(h_t, p^5)$ for $t \geq 1$. Let $\mathbf{1}\left(\cdot\right)$ be an indicator function. The choice functions at $t = 0$, pre- and post-policy change, are respectively denoted by

$$\begin{aligned} C^0_{pre}\left(h_0, p_0\right) &= \arg\max\nolimits_{p_1}\left\{-c\mathbf{1}(p_1 \neq p_0) + \delta \mathrm{E}\left[U^1\left(h_1, p_1\right)|h_0\right]\right\} \text{ and} \\ C^0_{post}\left(h_0, p_0\right) &= \arg\max\nolimits_{p_1}\left\{-c\mathbf{1}(p_1 \neq p_0) + \delta \mathrm{E}\left[V^1\left(h_1, p_1\right)|h_0\right]\right\}. \end{aligned} \tag{1.3}$$

[5] Individual subscripts are ommited. Assume H finite.

[6] As per Equation 1.9.

Proposition 1. *If beneficiaries face health risk, the policy change leads to a decrease in enrollment in p^5 (the 5-star plan) by the original deadline.*

The result follows from the observation that $\mathrm{E}\left[V^1\left(h_1,p_1\right)-U^1\left(h_1,p_1\right)|h_0\right]\geq 0$ holds for all plans, whereas for the 5-star plan $\mathrm{E}\left[V^1\left(h_1,p^5\right)-U^1\left(h_1,p^5\right)|h_0\right]=0$. The possibility of switching to the 5-star plan after the deadline increases, via option value, the payoff associated with enrollment in all plans—except that of the 5-star plan itself. The sole driver of the result within the model is the seemingly plausible assumption that health conditions might change.

The assumptions of the model, however, are not innocuous. Do beneficiaries know about and understand the policy change? How well do they know plan options? How well do they predict changes in their own health? How well do they assess the value of different plans for each possible future health state? Existing literature seems to suggest that the answer to at least some of these questions might be no. Abaluck and Gruber (2014, 2011) find that a majority of participants in Medicare Part D are enrolled in a plan that is dominated in terms of risk protection and costs, but fail to switch to a more suitable option. Handel and Kolstad (2014) provides evidence on the role of information frictions and hassle costs in health insurance choice.

Incorporating Present Bias

This section incorporates present bias in the model. I relax the canonical assumption of exponential time-discounting and apply hyperbolic time-discounting in its naive formulation (O'Donoghue and Rabin, 1999). At any given point in time, a present-biased beneficiary discounts payoffs to be accrued in the future by $\beta\leq 1$. That is in addition to the per-period discounting due to long-term impatience, δ. The beneficiary is naive: when considering inter-temporal decisions to be taken in the future, she fails to realize she will also then be present-biased. The model with present bias nests the fully-rational model as the special case $\beta=1$. In this model, the removal of the deadline for enrollment in the 5-star plan leads to a decrease in enrollment, even if the beneficiary doesn't face (or consider) health risks.

The choice functions at $t=0$, pre- and post- policy change, of a naive present-biased beneficiary are denoted respectively by

$$\begin{aligned}\tilde{C}^0_{pre}\left(h_0,p_0\right)&=\arg\max\nolimits_{p_1}\left\{-c\mathbf{1}(p_1\neq p_0)+\beta\delta\mathrm{E}\left[U^1\left(h_1,p_1\right)|h_0\right]\right\},\text{ and}\\ \tilde{C}^0_{post}\left(h_0,p_0\right)&=\arg\max\nolimits_{p_1}\left\{-c\mathbf{1}(p_1\neq p_0)+\beta\delta\mathrm{E}\left[V^1\left(h_1,p_1\right)|h_0\right]\right\}.\end{aligned}\tag{1.4}$$

Post-policy change, the beneficiary can switch to the 5-star plan at any time. As of an earlier period, she naively thinks that when t arrives, her continuation value will be $V^t(h_t,p_t)$, for $t\geq 1$. When time t arrives, however, the actual continuation value is given by

$$\tilde{V}^t(h_t,p_t)=u^t(h_t,p_t)+\max\left\{\beta\delta\mathrm{E}\left[V^{t+1}(h_{t+1},p_t)|h_t\right],-c+\beta\delta\mathrm{E}\left[U^{t+1}(h_{t+1},p^5)|h_t\right]\right\}.\tag{1.5}$$

Consider first a beneficiary whose health state is constant at h: she faces no health risk. Assume she is not enrolled in p^5 at $t = 0$, and that $p^\star$ is the plan which yields her the highest payoff.[7] Pre-policy change, said beneficiary enrolls in p^5 if switching costs are low enough: $c < \beta\delta\left(U^1\left(h, p^5\right) - U^1\left(h, p_0\right)\right)$. Post-policy change, the beneficiary has the possibility of switching to p^5 at any time. When making plans for behavior at a future time t, she naively anticipates switching to p^5, conditional on not having done so before, as long as $c < \delta\left(U^t\left(h, p^5\right) - U^t\left(h, p_0\right)\right)$. At time $t = 0$, a beneficiary who meets the previous condition thinks she will switch at $t = 1$. If $c > \frac{\beta\delta}{(1-\beta\delta)}\left(u(h, p^5) - u(h, p_0)\right)$, the anticipated discounted payoff from switching at $t = 1$ is higher than the payoff from switching at $t = 0$. Hence, she doesn't switch today and anticipates switching tomorrow. Given the stationarity of the setting under consideration, the same will-switch-tomorrow behavior (procrastination) takes place indefinitely.

Present bias decreases enrollment in the 5-star plan via an increase in inertia. The possibility of switching to a 5-star plan in the future decreases the perceived incentives to switch in the present and leads to procrastination.[8] Under the conditions of the previous paragraph, a beneficiary who would have switched to p^5 pre-policy change now procrastinates indefinitely if the following condition is met:

$$\frac{\beta\delta}{(1-\beta\delta)}\left(u(h, p^5) - u(h, p_0)\right) < c < \beta\delta\left(U^1\left(h, p^5\right) - U^1\left(h, p_0\right)\right). \tag{1.6}$$

Proposition 2. *If beneficiaries are present-biased and naive, the policy change leads to a decrease in enrollment in* p^5 *(the 5-star plan) even if there is no (perceived) health risk, assuming condition 1.6 is met.*

Let's now consider a present-biased beneficiary who faces a health risk. At $t = 0$, the beneficiary reasons about future behavior conditional on each possible future health state. Under contingency h_1, she anticipates switching to p^5 at $t = 1$ if $c < \delta E\left[U^2(h_2, p^5) - V^2(h_2, p_1)|h_1\right]$, but only switches when $t = 1$ arrives if $c < \beta\delta E\left[U^2(h_2, p^5) - V^2(h_2, p_1)|h_1\right]$. In this model, the policy decreases enrollment in p^5 for two reasons. First, there is an increase in the payoff associated with enrollment in all plans but p^5 due to the possibility of switching to p^5 after the original deadline—as in the model with no present bias. Second, the beneficiary overestimates her future willingness to switch to p^5, which decreases the incentive to switch in the present and increases inertia. Both mechanisms lead to a decrease in enrollment in the 5-star plan by the original deadline following the policy change.

In the model with present bias, the decrease in enrollment in 5-star plans following the policy change requires that beneficiaries know about and understand the policy change.

[7]Under the conditions considered, the policy change does not induce changes in the behavior of a beneficiary already enrolled or who has no incentives to switch to the 5-star plan.

[8]A sophisticated beneficiary who is fully aware of her future present bias will not procrastinate, but might delay enrollment.

For a discussion of the information about the policy change provided by CMS to Medicare beneficiaries, refer to Section 1.2 and Figure 1.1.

Summary of Testable Predictions

The results of the previous section are not dependent on particular assumptions with respect to $u^t(h_t, p_t)$ or the particular type of health risk faced by beneficiaries. In this section, I discuss simpler versions of the models that incorporate stylized facts from the Part D market and the Medicare population. The models introduced here have a richer set of testable predictions, at the expense of generality. Throughout this section, I focus on the behavior of an un-enrolled beneficiary. Given the large inertia observed in Part D among those previously enrolled in a plan, it is plausible to expect the response to the policy to be driven by changes in behavior of new Medicare beneficiaries, who join the program for the first time on the month they turn 65. Figure 1.3 summarizes the testible predictions of the simple models presented in this section.

Simplest Rational Option Value Model This section studies the behavior of a fully-rational un-enrolled beneficiary in a simple model with only two health conditions (healthy, sick) and three plans (5-star, non-5 star, and the outside option), and positive switching costs. The average 5-star plan has a larger premium and a lower deductible than other plans. Hence, I assume the 5-star plan yields a higher instantaneous payoff for the sick than the non-5 star plan, and vice versa. I assume that sick is an absorbing state, and that the healthy face a positive probability of becoming sick. The model is presented in Appendix A.2.

In this simple 2x3 model, the policy change leads to an increase in the payoff expected by the healthy from enrollment in the non-5 star plan and from the outside option. The policy doesn't change payoffs for the sick. Consider a healthy beneficiary who would have, pre-policy change, enrolled in the 5-star plan exclusively because of the risk of becoming sick. Post policy-change, by the original deadline, she either remains un-enrolled, or enrolls in the non-5 star plan. This change in behavior leads to an increase in adverse selection by the original deadline. After the original deadline, she might switch to the 5-star plan upon becoming sick. This leads to an increase in adverse selection after the original deadline. Predictions are summarized in Figure 1.3c.

Simplest Present Bias Model With Naivete This section discusses a model in which an un-enrolled present-biased beneficiary in a simple model with three plans (5-star, non-5 star, and the outside option), no health risk, and positive switching costs. I assume that the degree of present bias is not related to other fundamentals such as health status. This is a restrictive assumption. The model is presented in Appendix A.2.

Consider a naive beneficiary who would have, pre-policy change, enrolled in the 5-star plan. Post policy-change, she expects to enroll in the 5-star on the next period, conditional on not having done so by the original deadline. That decreases perceived incentives to enroll in the 5-star plan by the original deadline and might lead to procrastination. Now consider a beneficiary who would have, pre-policy change, enrolled in the non-5 star plan. Post policy-change, she might also expect to enroll in the 5-star on the next period, conditional on not having enrolled in the non-5 star plan by the original deadline. That expectation decreases perceived incentives to enroll in the non-5 star plan by the original deadline and might also lead to procrastination. In both cases, the increase in perceived incentives to switch in the future increases inertia by the original deadline. Predictions are summarized in Figure 1.3d. In a model with full sophistication about present bias, a beneficiary might delay enrollment, but will not procrastinate.

Simplest Random Forgetting Model This section discusses the intuition of how the behavior of a forgetful un-enrolled beneficiary is impacted by the policy. The policymaker implicitly had in mind a version of this model when the policy was designed. The beneficiary chooses among three plan options (5-star, non-5 star, and the outside option), faces no health risk, and pays a positive cost to switch plans.

Consider a naive beneficiary who, at any time, forgets to implement her preferred plan of action with probability $f \in [0, 1]$. This nests the rational model as the special case $f = 0$. In this model, a beneficiary forgets to enroll in her preferred plan by the original deadline with the same probability both pre- and post-policy change. Hence, the removal of deadlines for enrollment in 5-star plans does not lead to changes in behavior by the original deadline. Post-policy change, a beneficiary who forgot to take action by the original deadline still has the opportunity to enroll in the 5-star plan. The beneficiaries who would have enrolled in the 5-star plan had they not forgotten will now do so (at some point). Additionally, some beneficiaries who forgot to take action but for whom the 5-star plan was suboptimal by the original deadline might also now switch to the 5-star plan (at some point). Predictions are summarized in Figure 1.3b.

1.4 Data

I use detailed micro data on enrollment, health conditions, and cost of utilization from the universe of Medicare beneficiaries from 2009 to 2012, matched with information on all PDP's available in United States for the same period.

Individual beneficiary data come from the administrative Medicare Master Beneficiary Files. The base segment of the data includes information on (i) monthly Part D enrollment information,[9] (ii) yearly demographic information (state, county, zip code, date of birth, date of death, sex, race, age), (iii) monthly entitlement indicators for Medicare Parts A, B, and D, (iv) original and current reasons for entitlement (age, disability, or particular disease), (v) information on participation in other programs whose coverage interact with

[9]Enrollment in Medicare takes place on a monthly basis.

that of Medicare (e.g. Extra Help and Medicaid), and (v) information on alternative sources of drug coverage (e.g. employer-sponsored).

The beneficiary data include a chronic conditions segment, with end-of-the-year indicators on 27 common illnesses such as heart failure, diabetes, depression, and hypertension. Finally, the data also contain yearly information on utilization and payment amounts on a broad range of services that enable me to recover payments made by both the beneficiary and Medicare under Parts A, B, and D. Data on plan benefit package, premiums, cost sharing tiers, and service area come from the Medicare Part D Plan Characteristics Files.

Sample Restrictions

Medicare enrollment rules are complex. There are several exceptions to the typical enrollment rules discussed in Section 1.2. In 2012, almost a third of all beneficiaries received subsidies to pay for prescription drug coverage via the Medicare Extra Help program. Subsidized beneficiaries are automatically enrolled in a Part D plan if they fail to choose one voluntarily. These beneficiaries have been given the option to switch plans at any time since Medicare Part D was implemented in 2006. Hence, the policy change under consideration did not change enrollment rules as far as Extra Help beneficiaries are concerned. Other beneficiaries who face different enrollment rules are those with a disability or disabling condition and those who receive prescription drug benefits from another source of coverage deemed credible by Medicare. Furthermore, employer group health plans restrict access to employees of particular firms.

I have data on all 54.32 million beneficiaries observed in the period. I construct an Intermediate Sample, which excludes beneficiaries (i) who are un-enrolled or dropped Medicare Parts A or B, (ii) with a disability, (iii) with End-Stage Renal Disease, (iv) participating in other programs (Extra Help, state buy-in, or retiree drug subsidy), or (v) with access to an alternative source of credible coverage, resulting in 24.36 million beneficiaries. The Final Sample further further excludes beneficiaries enrolled in a plan whose coverage area does not include their home address, and data from all demonstration, special-needs, or employer-group health plans, resulting in 17.43 million beneficiaries. Table 1.1 presents descriptive statistics on the restricted sample of beneficiaries and plans. Note that 5-star plans have larger premiums and lower co-pays that non-5 star plans.

Out of the total 17.43 million beneficiaries in the final sample, 3.99 million joined Medicare in 2009-2012. Observations from the latter, in the year they joined Medicare, form my *New Beneficiaries* sample. All other observations form my *Continuing Beneficiaries* sample.

1.5 Effect on Enrollment

This section analyzes the impact on the policy on enrollment. I test the impact of the policy on enrollment in 5-star plans and take-up. I also test the predictions of the models of

Section 1.3. A summary of the claims and testable predictions is found on Figure 1.3. My identification strategy explores the time-series variation on the star rating of Part D insurers. I take advantage of the fact that not all counties in the United States were within the coverage area of an insurer that was rated 5 star in 2012—when the deadlines for enrollment in those plans were removed. Hence, the policy change did not *de facto* modify enrollment rules everywhere in the country. I employ a difference-in-differences design.

In Section 1.5, I assess the effect of the policy on the overall Medicare Part D take-up. Section 1.5 introduces and discusses the estimates of a version of the Berry (1994) differentiated-product discrete-choice demand framework which incorporating the absence of deadlines for enrollment as a time-varying plan characteristic. I use the discrete-choice estimation to evaluate impact of the policy on enrollment and market shares of 5-star and non-5 star plans in counties impacted by the policy.

Program Take-Up

This section analyzes the effect of the policy change on the take-up of Medicare Part D. Take-up in county c (region r) at time t is modeled as

$$ln\left(\frac{TakeUp_{ct}}{1-TakeUp_{ct}}\right) = \eta_1 FiveStar_{ct}^{\mathsf{cnty}} + \eta_2 FiveStar_{ct}^{\mathsf{cnty}} Post_t + \mathrm{X}_{ct}\alpha^{rt} + \xi_c + \vartheta_{rt} + u_{ct}, \quad (1.7)$$

where $FiveStar_{ct}^{\mathsf{cnty}}$ is an indicator for a county within the coverage area of a 5-star insurer, $Post_t$ is an indicator for the post-policy change period, X_{ict} are controls, and ξ_c and ϑ_{rt} are county and region-time fixed effects. All variables are measured at the time-county level. Depending on the goal of the analysis, time is either a month or a year. The control variables used are mean premium and deductible across plans, mean star-classification, average number of plans offered by, and total number of insurers. Each region r corresponds to the jurisdiction of a CMS regional office as per Figure 1.4. Standard errors are clustered at the state level.

The coefficient of interest is η_2, which captures the effect of the removal of the deadline for enrollment in 5-star plans on take-up. I identify that coefficient as the post-policy change differential impact (difference-in-differences) that being within the coverage area of a 5-star insurer has on county take-up. Predictions under the different hypothesized models are found in Figure 1.3.

At first, I do not distinguish between the effect before and after the original deadline. The purpose of not doing so is to estimate overall effects (column 3 of Figure 1.3). Table 1.2 presents the results of the specification in 1.7 using data at the month-county level. The estimates in column 4 indicate a drop in Part D participation of 4.92%. This result accounts for a drop of 2.55 percentage points in Medicare Part D take-up, from a baseline of 51.76%.

Table 1.3 evaluates the impact of the policy on take-up by the original deadline. I show results for new beneficiaries and for continuing beneficiaries, following the definition in Section 2.3. Among new beneficiaries, I find a 15.73% decrease in participation by the original deadline (column 2). For continuing beneficiaries, the estimated drop in participation by the original December 7th deadline is 3.63% (column 4). The results are equivalent to a drop of 6.63 (2.06) percentage points in take-up among new (continuing) beneficiaries, from a baseline of 42.2% (55.8%).

The difference in effect magnitudes between new and continuing enrollees can be attributed to the high inertia observed among beneficiaries previously enrolled in a plan (Section 1.3d), and possibly to a higher awareness of the policy among new beneficiaries. In fact, results in Table **??** confirm that the drop in enrollment decreases by age group. The effect is not statistically significant for those over 80 years old. Table A.3 presents the results of an analysis that uses publicly available data on take-up rates at the month-county level. As the last year currently available on the administrative micro data is 2012, I use the aggregate data to extend the post-policy change period by one year. The negative impact of the policy on take-up rates seem to be getting bigger over time. This could be due, among other plausible explanations, to an increase in awareness among beneficiaries about the policy change.

The decrease in the take-up of Medicare Part D–overall and by the original deadline–is consistent with the predictions of both the Option Value and Present Bias models. In the Option Value model, it is driven by relatively healthy beneficiaries who strategically respond to the policy change by delaying enrollment in a drug coverage because they can enroll in the 5-star plan if their health deteriorates before the next general enrollment opportunity. In the Present Bias model, it is driven by beneficiaries for whom the deadline encouraged action and who now procrastinate. The drop in take-up is not consistent with the Random Forgetting model, nor is it in line with the objectives the policymaker was designed to achieve.

Robustness Check In principle, it is possible that enrollment drops post-policy change in all counties with highly-rated insurers, and not exclusively in counties with 5-star plans. Here, I expand the specification in 1.7 to assess how enrollment varies, from pre- to post-policy change, with the maximum-star-rating-of-an-insurer-in-county. Take-up in county c (region r) at time t is modeled as

$$ln\left(\frac{TakeUp_{ct}}{1-TakeUp_{ct}}\right) = \sum_s \{\phi_s^{pre} M_{sct}(1-Post_t) + \phi_s^{post} M_{sct} Post_t\} + \mathrm{X}_{ct}\beta + \xi_c + \vartheta_t + u_{ct}, \quad (1.8)$$

where M_{sct} is an indicator for a county where maximum-ranked insurer is s-star. All other variables are as defined in Specification 1.7. Figures 1.5 and 1.6 plot the estimates ϕ^{pre} and ϕ^{post} for new and continuing beneficiaries, respectively. The post-policy change drop in enrollment happens exclusively in counties within the coverage area of a 5-star insurer. There is no drop in counties in which the highest-rated insurer received a 4.5 or 4.0 classification.

Plan Market Shares

This section introduces a version of the Berry (1994) differentiated-product aggregate discrete-choice demand model that I use to estimate the effect of the policy on the market shares of different drug coverage plans. The option for an aggregate framework is partially due to the impracticality of estimating an individual-level discrete choice model in the setting. Each county might have a different set of plans available, as Medicare Part D insurers have limited coverage areas. New plans are introduced on an annual basis. Existing plans might be terminated, split, or consolidated. Options abound. On average, a Medicare beneficiary could choose among over thirty plans in 2012. The option uses an aggregate model, however, is not without drawbacks. I discuss the limitations imposed by this modeling choice below.

I follow the notation and language in Nevo (2001). Consider beneficiary i, who lives in county c. For ease of notation, I initially omit the county subscript. She chooses one among the set options $\mathcal{P}_t$, which includes P_t plans plus the outside option. The indirect utility she derives from plan $p \in \mathcal{P}_t$ is given by

$$u_{ipt} = \mathrm{X}_{pt}\alpha + \xi_p + \vartheta_t + \lambda_{pt} + \epsilon_{ipt}, \tag{1.9}$$

where X_{pt} is a vector of observable plan characteristics, ξ_p and ϑ_t are respectively plan and time-specific deviations, λ_{pt} is a plan-time-specific deviation, and ϵ_{ipt} is a mean-zero stochastic term. Following standard normalizations, the indirect utility associated with the outside option is expressed as $u_{iot} = \epsilon_{iot}$. Assuming that the additive random shocks ϵ_{ipt} are independently, identically type I extreme value distributed, market shares s_{pt} can be shown to satisfy $ln(s_{pt}/s_{ot}) = \mathrm{X}_{pt}\alpha + \xi_p + \vartheta_t + \varepsilon_{pt}$. Combining all counties and letting α and ϑ_t be region-specific result in $ln\,(s_{pt}/s_{ot}) = \mathrm{X}_{pct}\alpha^r + \xi_{pc} + \vartheta_{rt} + \varepsilon_{pct}$, where r is a region subscript.

I estimate the impact of the removal of deadlines for enrollment in 5-star plans on market share of plan p in county c (region r) at time t on

$$\begin{split} ln\left(\frac{s_{pct}}{s_{oct}}\right) = \gamma_1 FiveStar_{ct}^{\mathsf{plan}} + \gamma_2(1 - FiveStar_{ct}^{\mathsf{plan}})FiveStar_{ct}^{\mathsf{cnty}} + \gamma_3 FiveStar_{ct}^{\mathsf{plan}} Post_t + \\ + \gamma_4(1 - FiveStar_{ct}^{\mathsf{plan}})FiveStar_{ct}^{\mathsf{cnty}} Post_t + \mathrm{X}_{pct}\beta + \xi_{pc} + \vartheta_t + u_{pct} \end{split}, \tag{1.10}$$

where s_{pct} is market share, s_{oct} is the share of un-enrolled beneficiaries, $FiveStar_{ct}^{\mathsf{plan}}$ indicates 5-star plans, $FiveStar_{ct}^{\mathsf{cnty}}$ indicates a county within the coverage area of a 5-star insurer, $Post_t$ is an indicator for the post-policy change, and X_{pct}, ξ_{pc}, and ϑ_t are plan characteristics, plan-county and time fixed effects, respectively. Plan characteristics include a rich set of variables that capture each plan's quality, benefits and costs. The typical design of a typical Medicare drug coverage plan is explained in detail in Section 1.2. The vector X_{ct} includes star rating dummies, premium, deductible, initial coverage limit, out-of-pocket cost threshold amount, among others. The full set of plan characteristics is listed on Table 1.5. Standard errors are clustered at the state level.

The parameters of interest are γ_3 and γ_4. The estimate of γ_3 identifies the differential impact (difference-in-differences) that the 5-star rating has on plan market shares, post-versus pre-policy change. I attribute that difference to the removal of deadlines for enrollment in 5-star plans. The estimate of γ_4 identifies the impact of the policy on average market share of plans that are not rated 5-star, but operate in a county in which at least one plan was rated 5-star. Table 1.5 presents the results of the specification in 1.10. I find a significant negative impact of the policy change on the market share of both 5-star and non-5-star plans, resulting in an increase in un-enrollment. These results hold for both continuing and new enrollees. For continuing beneficiaries, average market share of 5-star plans falls in 1.37 percentage points, from a baseline 7.78%.

Robustness Checks Analogously to the robustness checks in the analysis of take-up, I test how the star rating of a plan impacts market shares in the pre- and post-policy change period, as in

$$ln\left(\frac{s_{pct}}{s_{oct}}\right) = \sum_s \{\rho_s^{pre} R_{spct}(1 - Post_t) + \rho_s^{post} R_{spct} Post_t\} + \mathrm{X}_{pct}\beta + \xi_{pc} + \vartheta_t + u_{pct}, \tag{1.11}$$

where R_{spct} is an indicator for a plan rated s-star and all other variables are as defined in Specification 1.7. The estimates and 95% confidence interval of ρ_s^{pre} and ρ_s^{post} are plotted on Figure 1.7. Additionaly, Figure 1.8 depitcs the estimates of ς_{1s}, ς_{2s}, ς_{3s}, ς_{4s} in

$$\begin{aligned} ln\left(\tfrac{s_{pct}}{s_{oct}}\right) = \sum_s \{&\varsigma_{1s} R_{spct}(1 - FiveStar^{\textsf{cnty}})(1 - Post_t) + \varsigma_{2s} R_{spct} FiveStar^{\textsf{cnty}}(1 - Post_t) + \\ &+ \varsigma_{3s} R_{spct}(1 - FiveStar^{\textsf{cnty}}) Post_t + \varsigma_{4s} R_{spct} FiveStar^{\textsf{cnty}} Post_t\} + \\ &+ \mathrm{X}_{pct}\beta + \xi_{pc} + \vartheta_t + u_{pct} \end{aligned} . \tag{1.12}$$

1.6 Effect on Adverse Selection

In this section, I analyze the impact of the policy change on adverse selection. In the Option Value model of section 1.3, the drop in enrollment in 5-star plans is driven by changes in behavior of relatively healthy beneficiaries. The possibility of switching later discourage beneficiaries to enroll in a 5-star plan by the original deadline. After the deadline, beneficiaries might switch to a 5-star plan following a negative health shock. The decrease (increase) in enrollment by (after) the original deadline leads to an increase in adverse selection into 5-star plans. I test the implications of the Option Value model on adverse selection in two different ways.

First, I use cost services provided as a proxy for health condition. The hypothetical increase in adverse selection leads to a rise in the cost associated with 5-star plans. I model the average cost of the services associated with plan p in county t (region r) at year t as

$$\begin{aligned} ln\left(\tfrac{cost_{pct}}{cost_{oct}}\right) = &\varphi_1 FiveStar_{ct}^{\textsf{plan}} + \varphi_2(1 - FiveStar_{ct}^{\textsf{plan}}) FiveStar_{ct}^{\textsf{cnty}} + \varphi_3 FiveStar_{ct}^{\textsf{plan}} Post_t + \\ &+ \varphi_4(1 - FiveStar_{ct}^{\textsf{plan}}) FiveStar_{ct}^{\textsf{cnty}} Post_t + \mathrm{X}_{pct}\beta^r + \xi_{pc} + \vartheta_{rt} + u_{pct} \end{aligned} , \tag{1.13}$$

where $cost_{pct}$ is average cost associated with plan p, $cost_{oct}$ is average cost of those un-enrolled in drug coverage plan, $FiveStar^{\mathsf{plan}}_{ct}$ indicates 5-star plans, $FiveStar^{\mathsf{cnty}}_{ct}$ indicates a county within the coverage area of a 5-star plan, $Post_t$ indicates post-policy change, X_{pct} are controls, and ξ_{pc} and ϑ_{rt} are plan-county and time-region fixed effects, respectively. Standard errors are clustered at the state level.

To avoid moral hazard concerns, I use the average cost of the services provided under Medicare Parts A and B as outcome variable. This approach also enables me to observe the costs associated with Medicare beneficiaries who are not enrolled in a drug coverage plan. Table 1.6 presents the results of specification 1.13. I fail to reject the null-hypothesis of no impact of the policy change on adverse selection.

The second approach in which I test the impact of the policy on adverse selection uses end-of-the-previous-year chronic conditions indicators. I focus on the behavior of continuing enrollees—for whom the data is available—by the original deadline. I assess how changes in Part D participation vary from healthy individuals to those with specific chronic conditions such as heart failure, diabetes, and depression. Let Y_{ict} indicate individual participation in the Medicare Part D program of person i (county c) at time t. I use

$$Y_{ict} = \lambda_1 FiveStar^{\mathsf{cnty}}_{ct} + \lambda_2 FiveStar^{\mathsf{cnty}}_{ct} Post_t + \mathrm{X}_{ict}\beta^r + \xi_c + \vartheta_{rt} + u_{ict}, \tag{1.14}$$

where $FiveStar^{\mathsf{plan}}_{ct}$ indicates 5-star plans, $FiveStar^{\mathsf{cnty}}_{ct}$ indicates a county within the coverage area of a 5-star plan, $Post_t$ indicates post-policy change, X_{pct} are controls, and ξ_{pc} and ϑ_{rt} are plan-county and region-time fixed effects, respectively. Standard errors clustered by state.

Results of specification 1.14 are presented on table 1.7. Columns 1 and 2 present the result for beneficiaries who do not have chronic conditions and those with at lest one health condition.[10] The remaining columns compare those with a specific illness to those without it. I show results for chronic heart failure, diabetes, and depression. I do not find evidence in support of the Option Value model of section 1.3. For most conditions, the responses of the healthy and of the ill are of similar magnitude.

1.7 Effect on Inertia

In this section, I analyze the impact of the policy on inertia. In the Present Bias model of section 1.3, the possibility of switching to a 5-star plan in the future decreases perceived incentives to switch plans in the present, which leads to an increase in inertia. The rational model might also lead to an increase in inertia among un-enrolled beneficiaries, as they

[10]The chronic conditions observed are anemia, acquired hypothyroidism, asthma, atrial fibrillation, benign prostatic hyperplasia, cataracts, chronic heart failure, chronic kidney disease, chronic obstructive pulmonary disease, heart failure, hyperlipidemia, depression, diabetes, glaucoma hip/pelvic fracture, hypertension, ischemic heart disease, rheumatoid arthritis/osteoarthritis, stroke/transient ischemic attack, and the following types of cancer: breast, colorectal, prostate, lung, endometrial.

now wait to enroll only after a negative health event. Hence, I focus on the behavior of beneficiaries who are already enrolled in a drug coverage plan. I model inertia as

$$I_{ict} = \alpha_1 FiveStar_{ct}^{\mathsf{cnty}} + \alpha_2 FiveStar_{ct}^{\mathsf{cnty}} Post_t + \mathrm{X}_{ict}\beta^r + \xi_c + \vartheta_{rt} + u_{ict}, \tag{1.15}$$

where I_{ict} equals one if the beneficiary does not switch plans and zero otherwise, $FiveStar_{ct}^{\mathsf{cnty}}$ indicates a county within coverage area of 5-star insurer, $Post_t$ indicates the post-policy change period, X_{ict} are controls, and ξ_c and ϑ_{rt} are county and time fixed effects, respectively. Standard errors are clustered at the state level.

Table 1.8 presents the result of specification 1.15. Column 1 shows results for all beneficiaries who are already enrolled in a drug coverage plan before the original deadline. From a year to the next, plans are either renewed, terminated, split, or consolidated. Column 2 only keeps beneficiaries who were enrolled in plans that were renewed. Further, I restrict attention to beneficiaries who remained enrolled after the original deadline. This guarantees that I capture inertia at the plan choice margin, not at the program participation margin. Finally, I drop beneficiaries who might have a reason to change plans due to a change in home address.

Across specifications, I find that the policy change decreases the probability that a current enrollee switches plans by the original deadline in 3.18 percentage points, down from the average baseline of 9.08% switching probability. This results is consistent with the prediction of the Present Bias model of section 1.3.

1.8 Discussion

This paper analyzes the consequences of a policy change that removes deadlines for enrollment in high quality (5-star) Medicare Part D drug coverage plans. According to the Centers for Medicare and Medicaid Services (CMS), the objective of the policy was to "get beneficiaries into 5-star plans" (Moeller, 2011) and "give plans greater incentive to achieve 5-star status" (Crochunis, 2010). In this paper, I postulate that the policy might backfire for two non-mutually exclusive reasons. First, beneficiaries might now wait to enroll in 5-star plans only when a negative health event occurs. Second, without deadlines, beneficiaries might procrastinate. Both mechanisms would lead to a drop in 5-star plan enrollment.

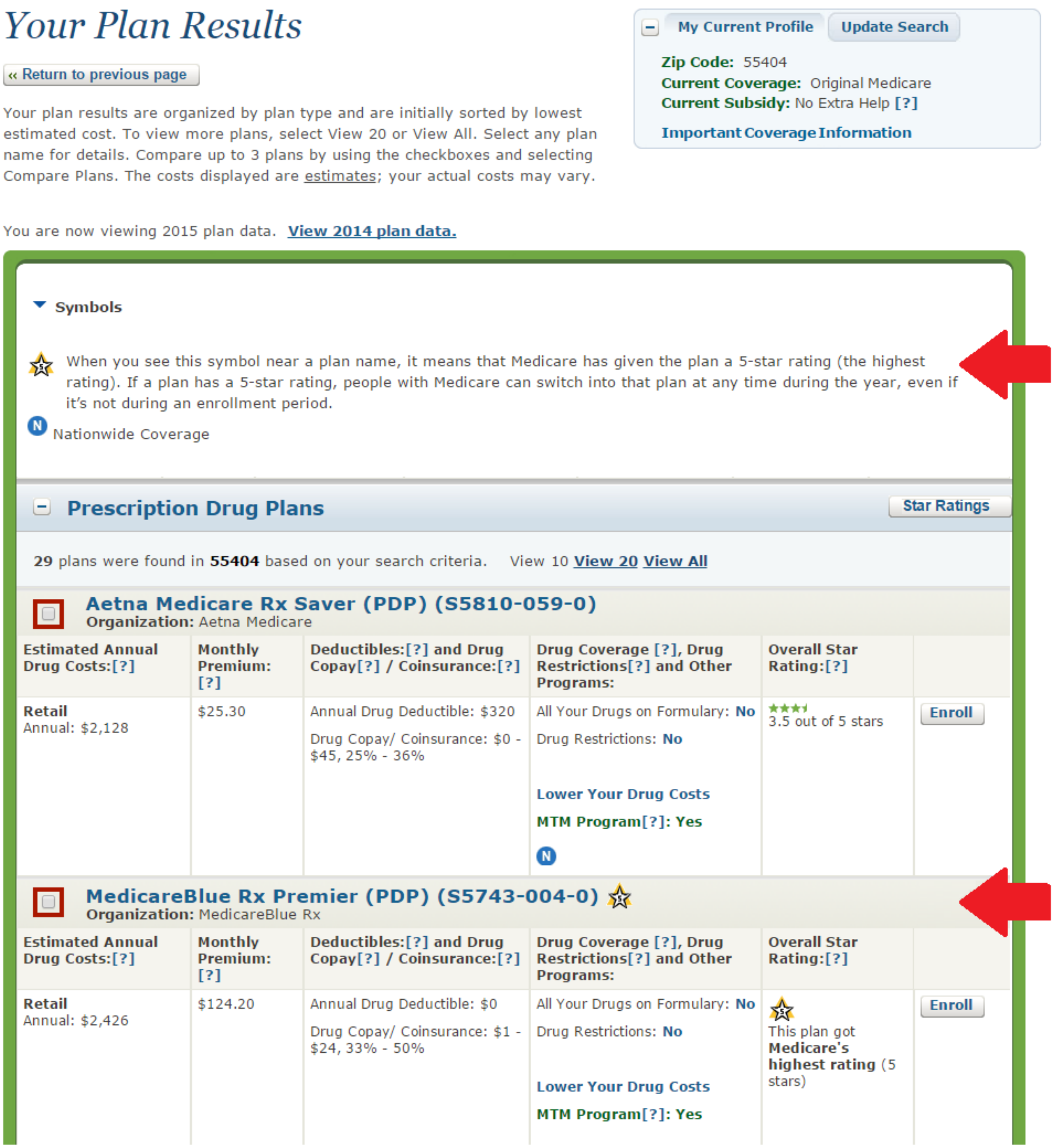
I introduce a fully-rational model to examine changes in behavior induced by the policy, then I expand the model to incorporate present bias. I test the predictions of the model using Medicare administrative micro data from 2009 to 2012. I employ a difference-in-differences design exploring the fact that policy did not modify enrollment rules everywhere in the country, as most counties in the United States were not within the coverage area of an insurer that was rated 5 star in 2012. I find that the policy backfires: it decreases enrollment in the Part D program by 2.55pp (baseline 51.76%), and decreases average market share of 5-star plans by 1.37pp (baseline 7.78%).

In the fully-rational model, the predicted drop in enrollment in 5-star plans requires that beneficiaries be aware of the policy change, know plan options, accurately predict changes in their own health, and assess the value of different plans for each possible future health state. I fail to find evidence supporting a core implication of this model: increase in adverse selection into 5-star plans. This result seems to be in line with existing literature (Abaluck and Gruber [2014, 2011], Handel and Kolstad [2014], Ericson [forthcoming]).

The underlying mechanism of the predicted drop in 5-star enrollment under present bias is an increase in inertia. Accordingly, I find that the policy change decreases the probability that a beneficiary already enrolled in Part D will switch plans by the original deadline in 3.18pp, down from the baseline switching probability of 9.08%. The predictions of the present bias model require that beneficiaries be aware of the policy change.

This paper contributes to the debate on behavioral-inspired policymaking. Governments of the U.K. and of the U.S. have recently set up nudge units that aim at incorporating insights from behavioral economics in the design of public policies. This movement sparked a strong reaction among some circles in academia and in the public debate. Critics warn behavioral-inspired policies might backfire because "bureaucrats and their bosses are as full of blind spots and weak spots as any of the people they govern" (Economist, 2014). However, behavioral-inspired policies predate the establishment of nudge units. The policy analyzed in this paper, for instance, was not designed by the Behavior Insights Team. Yet, it presumably drew inspiration from a non-rational hypothesis: forgetting. In doing so, the policymaker failed to take into account that the policy could backfire if beneficiaries were either more rational than expected, or irrational in an unanticipated way. I find evidence consistent with the latter. This suggests that in applying behavioral hypothesis to policy, it is important to do the kind of analysis for which nudge units were set up to do.

Figure 1.1: The Policy Change



Notes: Capture from Medicare's online plan finder tool. Partial list of standalone Part D plans available for 2015 in Minneapolis, MN. Red arrows added. Source: https://www.medicare.gov/find-a-plan, accessed 11/2/2014.

Figure 1.2: Deadline for Enrollment in a Medicare Part D Plan

A - New Beneficiaries

At age 65	Pre-2012	Post-2012
5-star plans	May	No Deadline
All others plans	May	May

beneficiaries born in February

B - Continuing Beneficiaries

Annually	Pre-2012	Post-2012
5-star plans	December	No Deadline
All others plans	December	December

all beneficiaries

Notes: New beneficiaries may enroll in a plan until the end of the third month after they turn 65. Figure 2.A depicts the initial deadline for beneficiaries who join Medicare in February. All beneficiaries are allowed to enroll, drop, or switch plans once a year during Open Enrollment Period. Figure 2.B depicts the annual deadline to request changes in coverage for continuing beneficiaries. Since 01/2012, beneficiaries may enroll in a 5-star plan at any time.

Figure 1.3: Effect of the Policy Change on Enrollment

(a) Intended Consequences

	By Original Deadline	After Original Deadline	Overall
5-star Plans		↑	↑
Other Plans		=	
Total Take-Up		↑	↑

(b) Random Forgetting Model

	By Original Deadline	After Original Deadline	Overall
5-star Plans	=	↑	↑
Other Plans	=	=	=
Total Take-Up	=	↑	↑

(c) Option Value Model

	By Original Deadline	After Original Deadline	Overall
5-star Plans	↓	↑	↓↑
Other Plans	↓↑	=	↓↑
Total Take-Up	↓	↑	↓↑

(d) naive Present Bias Model

	By Original Deadline	After Original Deadline	Overall
5-star Plans	↓	=	↓
Other Plans	↓	=	↓
Total Take-Up	↓	=	↓

Notes: This figure contrasts the intended consequences of the policy change and the predictions of three different models. Figure 1.3a displays the goals of the Centers for Medicare and Medicaid Services (CMS). Figures 1.3b-1.3d depict the predictions of the models of Section 1.3. Figure 1.3b displays the predictions of the random forgetting model. Figure 1.3c displays the predictions of the option value model. Figure 1.3d displays the predictions of the present bias model.

Figure 1.4: Insurers, Counties, and Regions Affected

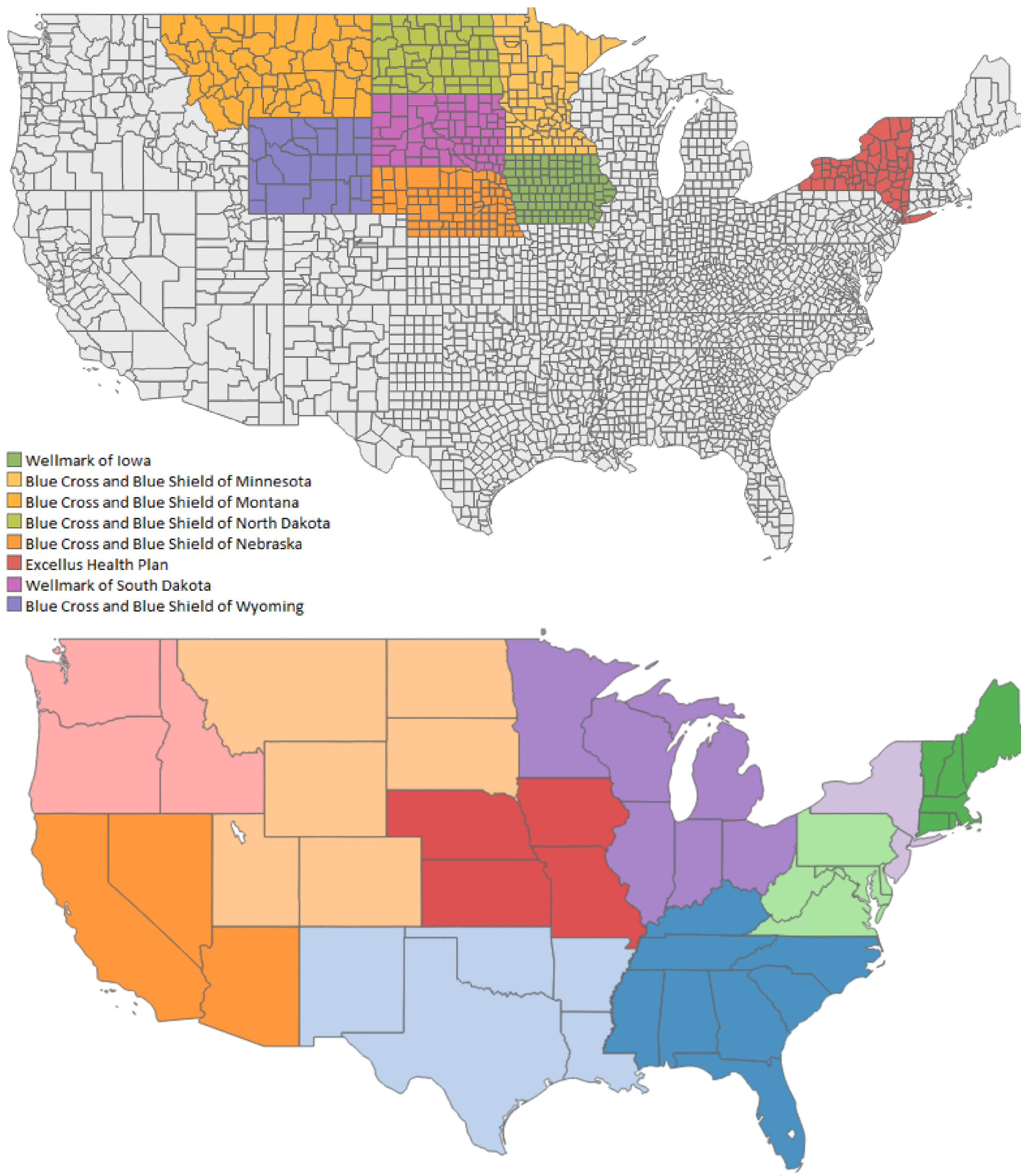
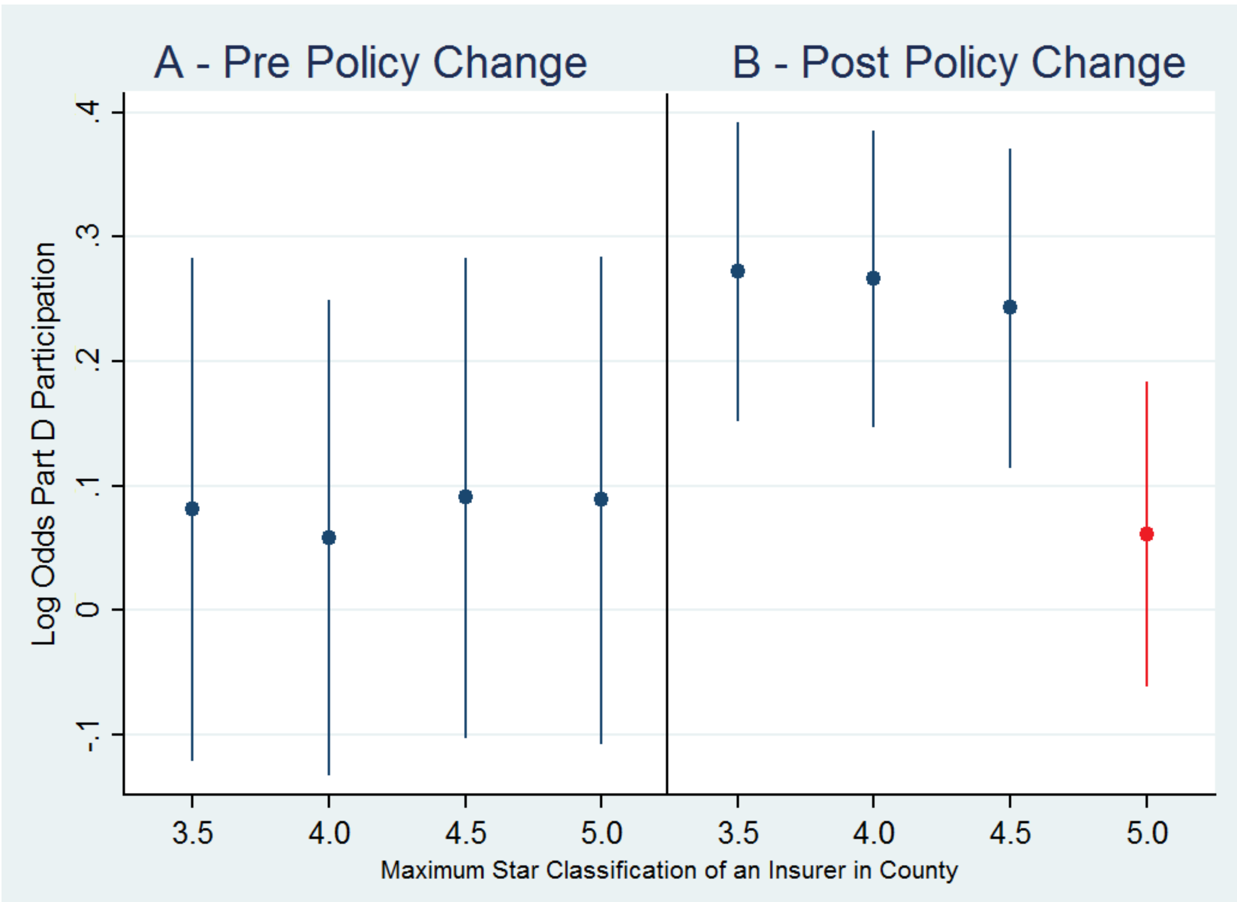
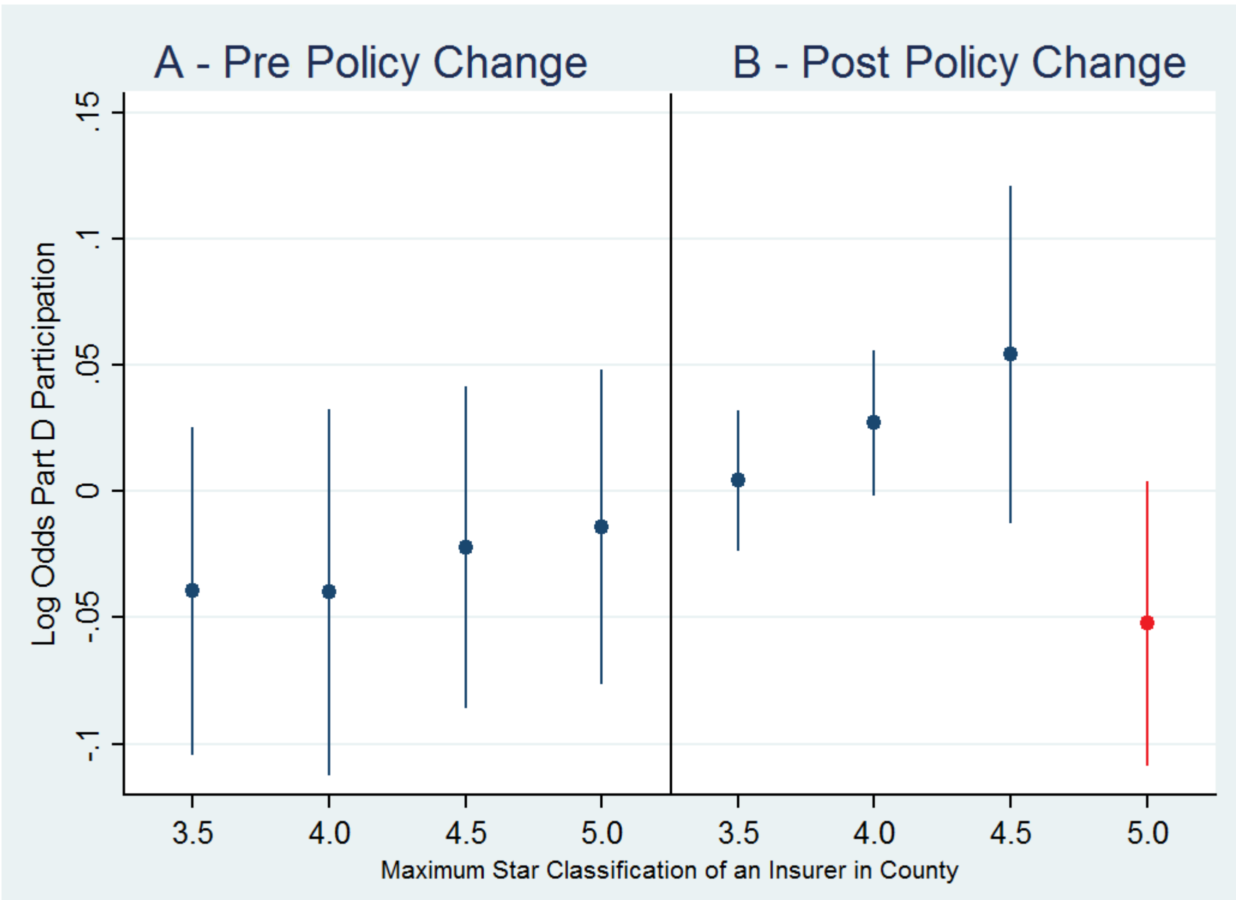


Figure 1.5: Effect of Maximum-Star-In-County on Take-Up of New Beneficiaries



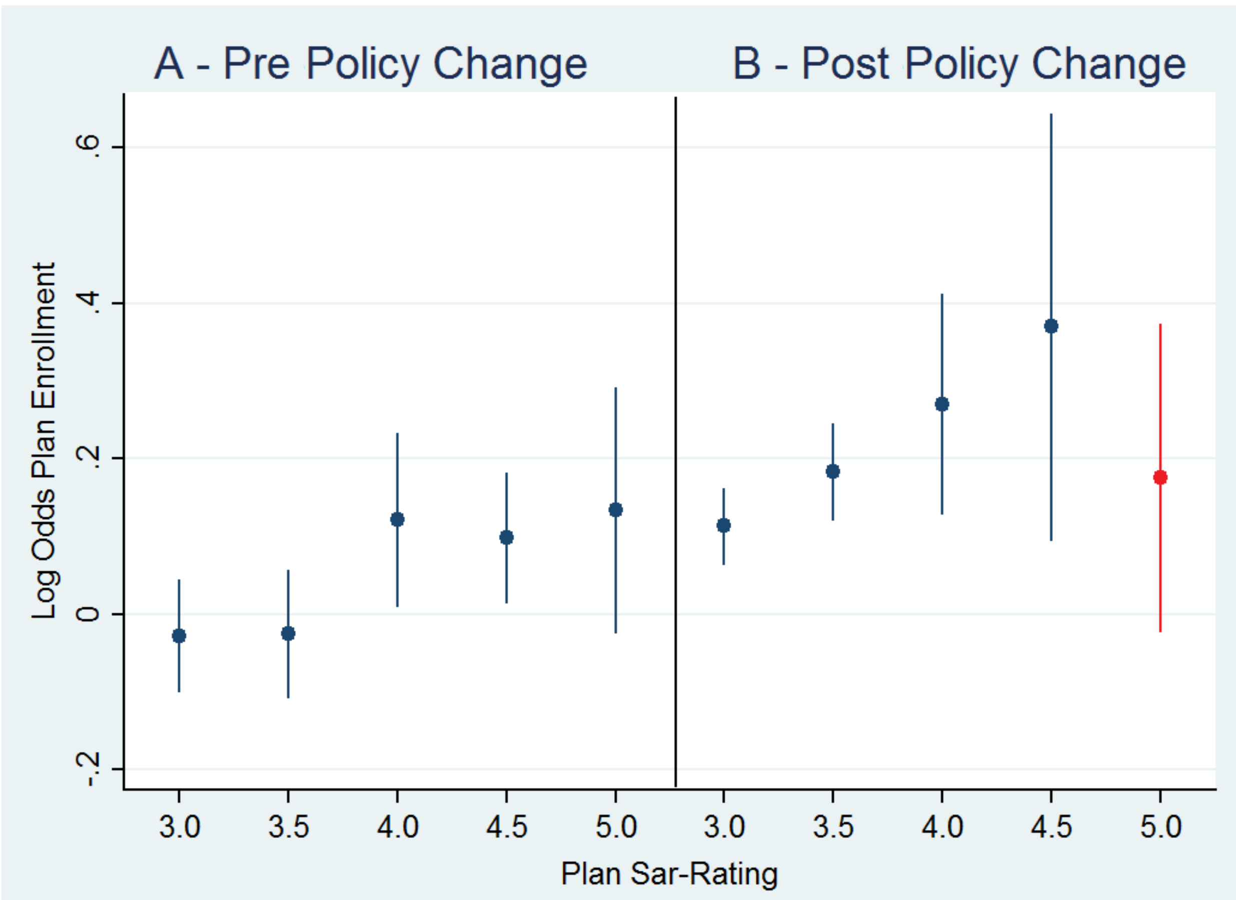
Notes: Estimates and 95% confidence intervals of ϕ^{pre} and ϕ^{post} on Equation 1.8, using data on new beneficiaries**.** Each observation is measured at the county-year level. The control variables included are mean premium and deductible of Part D plans, as well as mean star-classification, average number of plans offered by, and total number of Part D insurers. All controls are interacted with year and region fixed effects. Specification includes region-year fixed-effects. Unweighted. The omitted category includes all county-year observations with no insurer ranked higher than 3.0 stars. County divisions follow the Social Security Administration classification. Excludes beneficiaries not enrolled or who drop Medicare Parts A or B, with a disability, or with End-Stage Renal Disease. Excludes beneficiaries participating in Medicaid, state buy-in programs, retiree drug subsidy programs, or with access to an alternative source of credible drug coverage. Excludes beneficiaries enrolled in a plan whose coverage area does not include their home address. Excludes demonstration, special-needs, or employer-group health plans. Standard errors are clustered at the state level.

Figure 1.6: Effect of Maximum-Star-In-County on Take-Up of Continuing Beneficiaries



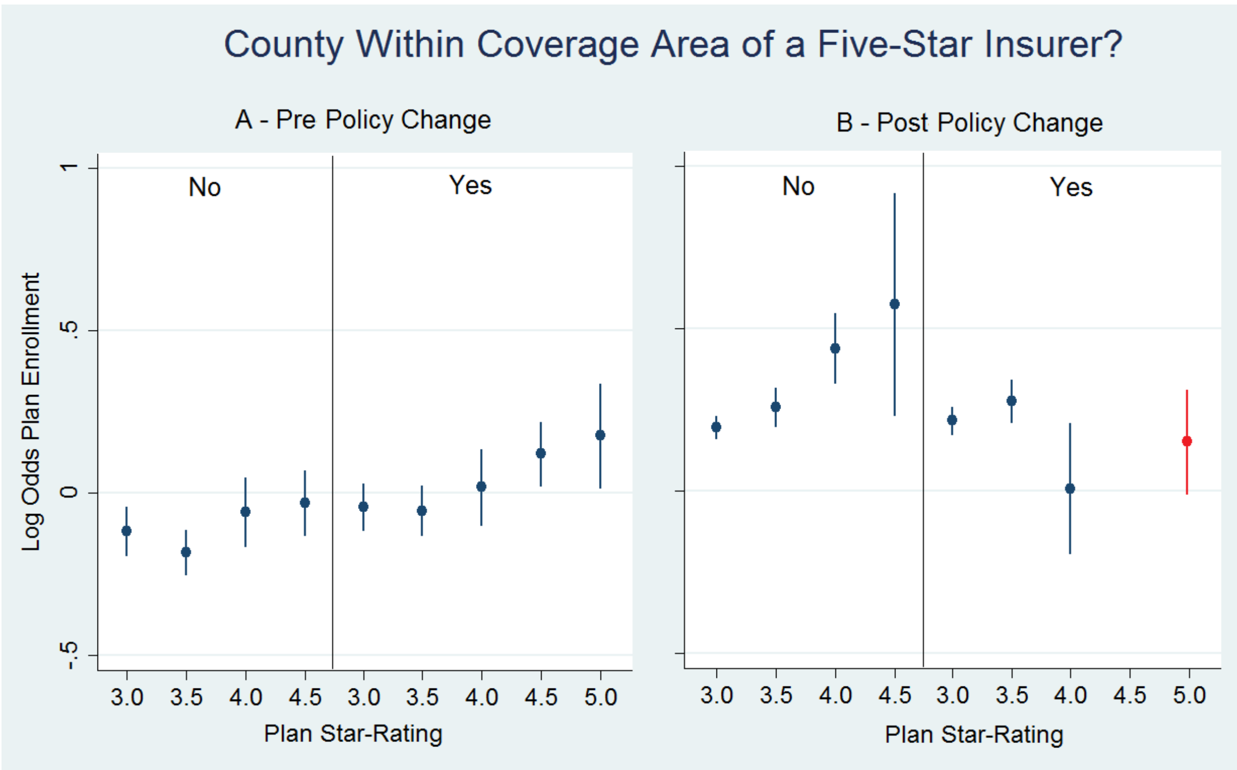
Notes: Estimates and 95% confidence intervals of ϕ^{pre} and ϕ^{post} on Equation 1.8, using data on continuing beneficiaries. Each observation is measured at the county-year level. The control variables included are mean premium and deductible of Part D plans, as well as mean star-classification, average number of plans offered by, and total number of Part D insurers. All controls are interacted with year and region fixed effects. Specification includes region-year fixed-effects. Unweighted. The omitted category includes all county-year observations with no insurer ranked higher than 3.0 stars. County divisions follow the Social Security Administration classification. Excludes beneficiaries not enrolled or who drop Medicare Parts A or B, with a disability, or with End-Stage Renal Disease. Excludes beneficiaries participating in Medicaid, state buy-in programs, retiree drug subsidy programs, or with access to an alternative source of credible drug coverage. Excludes beneficiaries enrolled in a plan whose coverage area does not include their home address. Excludes demonstration, special-needs, or employer-group health plans. Standard errors are clustered at the state level.

Figure 1.7: Effect of Star-Rating on Plan Choice



Notes: Estimates and 95% confidence intervals of ρ^{pre} and ρ^{post} on Equation 1.11, using data on all beneficiaries. Each observation is measured at the county-month level. The control variables included are mean premium and deductible of Part D plans, as well as mean star-classification, average number of plans offered by, and total number of Part D insurers. All controls are interacted with year and region fixed effects. Specification includes region-year fixed-effects. Unweighted. The omitted category includes all county-year observations with no insurer ranked higher than 3.0 stars. County divisions follow the Social Security Administration classification. Excludes demonstration, special-needs, or employer-group health plans. Standard errors are clustered at the state level.

Figure 1.8: Effect of Star-Rating on Plan Choice, by Coverage Area of 5-star Insurers



Notes: Post-policy change, coverage areas of 4.5- and 5.0-star insurers do not overlap. Estimates and 95% confidence intervals of ς_{1s}, ς_{2s}, ς_{3s}, ς_{4s} on Equation 1.12, using data on all beneficiaries. Each observation is measured at the county-month level. The control variables included are mean premium and deductible of Part D plans, as well as mean star-classification, average number of plans offered by, and total number of Part D insurers. All controls are interacted with year and region fixed effects. Specification includes region-year fixed-effects. Unweighted. The omitted category includes all county-year observations with no insurer ranked higher than 3.0 stars. County divisions follow the Social Security Administration classification. Excludes demonstration, special-needs, or employer-group health plans. Standard errors are clustered at the state level.

Table 1.1: Descriptive Statistics of Final Sample

A - County-Level

	Pre (2009-2011)		Post (2012)	
5-star county?	*Yes*	*No*	*Yes*	*No*
Take-Up	0.48	0.47	0.57	0.48
	(0.12)	(0.16)	(0.12)	(0.15)
Number of insurers	14.05	13.47	10.23	13.68
	(4.14)	(5.29)	(4.47)	(4.31)
Plans per insurer	1.39	1.53	1.35	1.45
	(0.17)	(0.30)	(0.12)	(0.18)
Eligibles (x1000)	18.8	13.2	10.1	17.0
	(46.2)	(37.1)	(32.1)	(44.8)

B - Plan-Level

	Pre (2009-2011)		Post (2012)	
*5-star plan?**	*Yes*	*No*	*Yes*	*No*
Premium	53.3	43.0	63.9	47.4
	(23.6)	(20.5)	(32.4)	(26.2)
Deductible	248.99	111.85	118.44	139.98
	(101.44)	(134.33)	(91.59)	(150.75)
Market share	2.53	1.98	7.78	2.13
	(2.9)	(2.5)	(8.0)	(2.8)

C - Individual-Level

	Pre (2009-2011)		Post (2012)	
5-star county?	*Yes*	*No*	*Yes*	*No*
Age	77.34	76.49	77.68	77.68
	(7.82)	(7.70)	(7.74)	(8.07)
Female (%)	64.73	65.01	65.22	67.80
Black (%)	1.09	2.67	0.20	1.40
Asian (%)	0.42	0.52	0.22	0.85
Hispanic (%)	0.67	1.87	0.26	1.30
Native American (%)	0.09	0.14	0.08	0.17
Total observations	53,475,333			

Notes: Averages. (*) Data from counties within the coverage area of a 5-star insurer.

Table 1.2: Monthly County-Level Take-Up of Medicare Part D (Jan 2009-Dec 2012)

$ln\,(TakeUp/\,(1-TakeUp))$	(1)	(2)	(3)	(4)
$\text{FiveStar}^{\text{cnty}}$	-0.000403	-0.00357	-0.000693	-0.0166
	(0.0119)	(0.0179)	(0.0125)	(0.0123)
$\text{FiveStar}^{\text{cnty}}\text{Post}$	**-0.0532****	**-0.143******	**-0.0937******	**-0.102*****
	(0.0289)	**(0.0448)**	**(0.0283)**	**(0.0427)**
Controls				
× Region FE	x	x	x	
× Region-Year FE				x
Region-Year FE	x	x	x	x
Average Effect	**-0.0132***	**-0.0357*****	**-0.0234*****	**-0.0254****
	(0.0154)	**(0.0214)**	**(0.0137)**	**(0.0206)**
Sample	All	Intermediate	Final	
Observations	152,904	152,822	152,788	152,788
Average Take-Up	0.4681	0.5227	0.5176	0.5176
R-squared	0.278	0.303	0.499	0.560
Number of SSA Counties	3,186	3,185	3,184	3,184
Number of Beneficiaries	54.32mi	24.36mi	17.43mi	17.43mi

Notes: Each observation is measured at the county-month level. The parameter of interest is the coefficient on $\text{FiveStar}^{\text{cnty}}\text{Post}$. $\text{FiveStar}^{\text{cnty}}$ is an indicator variable for the presence of a 5-star Part D insurer in county. Post is an indicator for post-policy change. The control variables included are mean premium and deductible of Part D plans, as well as mean star-classification, average number of plans offered by, and total number of Part D insurers. All specifications include county and time fixed effects. Sample Description: *Intermediate* excludes beneficiaries (i) who are un-enrolled or dropped Medicare Parts A or B, (ii) with a disability, (iii) with End-Stage Renal Disease, (iv) participating in other programs (Medicaid, state buy-in, retiree drug subsidy), or (v) with access to an alternative source of credible coverage; *Final* further excludes beneficiaries enrolled in a plan whose coverage area does not include their home address, and excludes data from demonstration, special-needs, or employer-group health plans. County divisions follow the Social Security Administration classification. Standard errors are clustered at the state level.

Table 1.3: Yearly County-Level Take-Up of Medicare Part D (2009-2012)

$ln\left(TakeUp/\left(1-TakeUp\right)\right)$	A - New Beneficiaries		B - Continuing Beneficiaries	
	(1)	(2)	(3)	(4)
FiveStar$^{\mathsf{cnty}}$	0.0279*	0.0337**	0.00909	0.00490
	(0.0162)	(0.0136)	(0.00620)	(0.00694)
FiveStar$^{\mathsf{cnty}}$Post	**-0.246*****	**-0.272*****	**-0.0797*****	**-0.0822*****
	(0.0652)	**(0.0786)**	**(0.0175)**	**(0.0193)**
Controls				
× Region FE	x		x	
× Region-Year FE		x		x
Region-Year FE	x	x	x	x
Average Effect	-0.060***	-0.066***	-0.019***	-0.020***
	(0.0377)	(0.0454)	(.0077)	(0.0085)
Sample	Final	Final	Final	Final
Observations	10,224	10,224	12,728	12,728
Average Take-Up	0.422	0.422	0.558	0.558
R-squared	0.166	0.202	0.269	0.354
Number of SSA Counties	2,556	2,556	3,182	3,182
Number of Beneficiaries	3.99mi	3.99mi	16.18mi	16.18mi

Notes: Each observation is measured at the county-year level. The parameter of interest is the coefficient on FiveStar$^{\mathsf{cnty}}$Post. FiveStar$^{\mathsf{cnty}}$ is an indicator variable for the presence of a 5-star Part D insurer in county. Post is an indicator for post-policy change. The control variables included are mean premium and deductible of Part D plans, as well as mean star-classification, average number of plans offered by, and total number of Part D insurers. All specifications include county and time fixed effects. County divisions follow the Social Security Administration classification. Excludes beneficiaries not enrolled or who drop Medicare Parts A or B, with a disability, or with End-Stage Renal Disease. Excludes beneficiaries participating in Medicaid, state buy-in programs, retiree drug subsidy programs, or with access to an alternative source of credible drug coverage. Excludes beneficiaries enrolled in a plan whose coverage area does not include their home address. Excludes demonstration, special-needs, or employer-group health plans. Standard errors are clustered at the state level.

Table 1.5: County-Level Market Shares of Medicare Part D Plans (2009-2012)

$ln\,(share)$	A - New Beneficiaries			B - Continuing Beneficiaries		
	(1)	(2)	(3)	(4)	(5)	(6)
Star Ratings Dummies	x	x	x	x	x	x
$(1-\text{FiveStar}^{\text{plan}})\,\text{FiveStar}^{\text{cnty}}$	0.0442**	0.0396**	0.0337**	0.00415	-0.00140	-0.00277
	(0.0173)	(0.0179)	(0.0137)	(0.00965)	(0.00771)	(0.00612)
$\text{FiveStar}^{\text{plan}}\text{Post2012}$	**-0.235***	**-0.334****	**-0.601****	**-0.0761***	**-0.159*****	**-0.179***
	(0.138)	**(0.145)**	**(0.229)**	**(0.0445)**	**(0.0563)**	**(0.100)**
$(1-\text{FiveStar}^{\text{plan}})\,\text{FiveStar}^{\text{cnty}}\text{Post2012}$	-0.156***	-0.119**	-0.0821**	-0.0535**	-0.0597***	-0.0304
	(0.0560)	(0.0560)	(0.0370)	(0.0202)	(0.0210)	(0.0252)
Controls	x			x		
× Region FE		x			x	
× Region-Year FE			x			x
Year-Region FE	x	x	x	x	x	x
Sample	Final	Final	Final	Final	Final	Final
Observations	137,930	137,287	136,817	349,249	348,958	348,540
R-squared	0.477	0.515	0.616	0.345	0.389	0.547
Number of Plan-Counties	91,038	90,671	90,389	178,938	178,834	178,691

Notes: Each observation is measured at the plan-county-year level. The dependent variable is $\ln(s_{pct}/s_{oct})$, where s_{pct} is plan market share and s_{oct} is the proportion of un-enrolled in county. All specifications include a complete set of dummies for plan star-rating. The parameter of interest is the coefficient on $\text{FiveStar}^{\text{plan}}\text{Post}$ and on $(1-\text{FiveStar}^{\text{plan}})\text{FiveStar}^{\text{cnty}}\text{Post}$. $\text{FiveStar}^{\text{plan}}$ is an indicator for 5-star plan.$\text{FiveStar}^{\text{cnty}}$ is an indicator variable for the presence of a 5-star Part D insurer in county. Post is an indicator for post-policy change. The control variables are total premium (basic + supplemental) rate (net of rebates), deductible amount, a dummy for no deductible, type of coverage offered in the gap, out-of-pocket cost threshold amount, initial coverage limit, and dummies for national coverage, premium below the regional benchmark, reduced post out-of-pocket threshold cost sharing amounts, reduced pre-ICL cost sharing amounts, reduced deductible amount, reduced cost sharing below Medicare standard, how plan applies cost sharing in the catastrophic coverage phase. All specifications include plan-county and time fixed effects. County divisions follow the Social Security Administration classification. Excludes beneficiaries not enrolled or who drop Medicare Parts A or B, with a disability, or with End-Stage Renal Disease. Excludes beneficiaries participating in Medicaid, state buy-in programs, retiree drug subsidy programs, or with access to an alternative source of credible drug coverage. Excludes beneficiaries enrolled in a plan whose coverage area does not include their home address. Excludes demonstration, special-needs, or employer-group health plans. Standard errors are clustered at the state level.

Table 1.6: Test of Adverse Selection - Average Medicare Parts A and B Cost of the Enrollees of Part D Plans (2009-2012)

$ln\,(cost)$	A - New Beneficiaries			B - Continuing Beneficiaries		
	(1)	(2)	(3)	(4)	(5)	(6)
Paid by	Total	Medicare	Beneficiary	Total	Medicare	Beneficiary
$\text{FiveStar}^{\text{plan}}$	0.0713	0.0928	0.0694	-0.0199	-0.0173	-0.0220
	(0.0778)	(0.0866)	(0.0611)	(0.0269)	(0.0287)	(0.0231)
$\left(1-\text{FiveStar}^{\text{plan}}\right)\text{FiveStar}^{\text{cnty}}$	-0.0237	-0.0231	-0.0250	3.93e-05	0.00297	-0.00701
	(0.0315)	(0.0352)	(0.0226)	(0.0265)	(0.0281)	(0.0242)
$\text{FiveStar}^{\text{plan}}\text{Post2012}$	**0.0647**	**0.0699**	**0.0312**	**-0.0452**	**-0.0537***	**-0.00516**
	(0.0707)	**(0.0673)**	**(0.0609)**	**(0.0289)**	**(0.0306)**	**(0.0269)**
$\left(1-\text{FiveStar}^{\text{plan}}\right)\text{FiveStar}^{\text{cnty}}\text{Post12}$	0.101**	0.106**	0.0827**	-0.0106	-0.0127	0.00536
	(0.0425)	(0.0459)	(0.0342)	(0.0277)	(0.0304)	(0.0228)
Year-Region FE	x	x	x	x	x	x
Sample	Final	Final	Final	Final	Final	Final
Observations	137,930	137,287	136,817	349,249	348,958	348,540
R-squared	0.010	0.009	0.011	0.011	0.011	0.010
Number of Plan-Counties	91,038	90,671	90,389	178,938	178,834	178,691

Notes: Each observation is measured at the plan-county-year level. The dependent variable is $\ln\left(\text{cost}_{\text{pct}}/\text{cost}_{\text{oct}}\right)$, where cost_{pct} is the average Medicare Parts A and B cost of enrollees of a Part D plan and cost_{oct} is the average Parts A+B cost of those in county who are un-enrolled in Part D. The parameter of interest is the coefficient on $\text{FiveStar}^{\text{plan}}\text{Post}$. $\text{FiveStar}^{\text{plan}}$ is an indicator for 5-star plan. $\text{FiveStar}^{\text{cnty}}$ is an indicator variable for the presence of a 5-star Part D insurer in county. Post is an indicator for post-policy change. All specifications include plan-county and time fixed effects. County divisions follow the Social Security Administration classification. Excludes beneficiaries not enrolled or who drop Medicare Parts A or B, with a disability, or with End-Stage Renal Disease. Excludes beneficiaries participating in Medicaid, state buy-in programs, retiree drug subsidy programs, or with access to an alternative source of credible drug coverage. Excludes beneficiaries enrolled in a plan whose coverage area does not include their home address. Excludes demonstration, special-needs, or employer-group health plans. Standard errors are clustered at the state level.

Table 1.7: Participation Decision, by Chronic Condition (2009-2012)

Participation indicator	Any Chronic Condition		Chronic Heart Failure		Diabetes	
	No	Yes	No	Yes	No	Yes
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{FiveStar}^{\text{cnty}}$	3.52e-05	0.000832	0.000456	0.00179	0.000753	0.000740
	(0.00271)	(0.00133)	(0.000998)	(0.00338)	(0.00109)	(0.00178)
$\text{FiveStar}^{\text{cnty}}\text{Post}$	**-0.0286*****	**-0.00748****	**-0.0110*****	**-0.0119***	**-0.0104*****	**-0.0126*****
	(0.00631)	**(0.00295)**	**(0.00261)**	**(0.00645)**	**(0.00239)**	**(0.00454)**
Controls						
× Region-Year FE	x	x	x	x	x	x
Region-Time FE	x	x	x	x	x	x
Sample	Final	Final	Final	Final	Final	Final
Observations	3,648,208	25,443,774	25,497,460	3,594,522	22,748,946	6,343,036
R-squared	0.034	0.007	0.015	0.007	0.016	0.009
Number of SSA Counties	3,196	3,199	3,198	3,195	3,197	3,198

Notes: Each observation is measured at the beneficiary-year level. The parameter of interest is the coefficient on $\text{FiveStar}^{\text{cnty}}\text{Post}$. $\text{FiveStar}^{\text{cnty}}$ is an indicator variable for the presence of a 5-star Part D insurer in county. Post is an indicator for post-policy change. The control variables included are mean premium and deductible of Part D plans, as well as mean star-classification, average number of plans offered by, and total number of Part D insurers. All specifications include county and time fixed effects. County divisions follow the Social Security Administration classification. Excludes beneficiaries not enrolled or who drop Medicare Parts A or B, with a disability, or with End-Stage Renal Disease. Excludes beneficiaries participating in Medicaid, state buy-in programs, retiree drug subsidy programs, or with access to an alternative source of credible drug coverage. Excludes beneficiaries enrolled in a plan whose coverage area does not include their home address. Excludes demonstration, special-needs, or employer-group health plans. Standard errors are clustered at the state level.

Table 1.8: Individual-Level Inertia (2009-2012)

$1 - Switch$ *[no-switch indicator]*	Continuing Beneficiaries (enrolled in plan that is renewed)				
	(1)	(2)	(3)	(4)	(5)
FiveStar$^{\mathsf{cnty}}$	0.000402	-0.0142	-0.0154	-0.0162	-0.0163
	(0.0125)	(0.0112)	(0.0124)	(0.0123)	(0.0124)
FiveStar$^{\mathsf{cnty}}$ × Post	**0.0224**	**0.0323**	**0.0372***	**0.0316***	**0.0318***
	(0.0250)	**(0.0198)**	**(0.0202)**	**(0.0188)**	**(0.0190)**
Controls	x	x			
× Region FE			x	x	x
Region-Time FE		x	x	x	x
Restrictions on beneficiaries:					
Remains enrolled in a plan				x	x
Does not change zip code					x
Sample	Final	Final	Final	Final	Final
Observations	16,430,238	16,430,238	16,430,238	16,042,973	15,340,597
Average Inertia	0.8873	0.8873	0.8873	0.9090	0.9092
R-squared	0.016	0.017	0.018	0.017	0.017
Number of SSA Counties	3,538	3,538	3,538	3,538	3,533

Notes: Each observation is measured at the individual-year level. Continuing beneficiaries may change their Part D coverage during Oct 15th-Dec 7th, changes are implemented on Jan 1st of the following year. The dependent variable is an indicator for not making changes during this period. The control variables included are number of plans available (quadratic), number of insurers available (quadratic), age and race dummies. Excludes beneficiaries not initially enrolled in a Part D plan. Excludes new beneficiaries. FiveStar$^{\mathsf{cnty}}$ is an indicator variable for a county within the coverage area of a 5-star Part D insurer. The variable of interest is FiveStar$^{\mathsf{cnty}}$Post, where Post is an indicator for the post-policy change period. All specifications include county and time fixed effects. County divisions follow the Social Security Administration classification. Excludes beneficiaries not enrolled or who drop Medicare Parts A or B, with a disability, or with End-Stage Renal Disease. Excludes beneficiaries participating in Medicaid, state buy-in programs, retiree drug subsidy programs, or with access to an alternative source of credible drug coverage. Excludes beneficiaries enrolled in a plan whose coverage area does not include their home address. Excludes demonstration, special-needs, or employer-group health plans. Standard errors are clustered at the state level.

Chapter 2

Weather, Mood, and Use of Antidepressants: The Role of Projection Bias in Mental Health Care Decisions

2.1 Introduction

Each year, 6.5% of adults in the United States suffer from major depression, 60% of which report having symptoms severe enough to keep them from performing daily tasks (Kressner et al., 2003). Yet little is known about the behavior of patients under treatment for major depression. This paper focuses on a specific behavioral bias likely to play a role in the choice of antidepressant treatment: the extent to which individuals separately identify the part of their current psychological well-being that is due to structural factors and those due to temporary conditions. Do individuals react to temporary conditions as if they were permanent? The standard model typically assumes that individuals are able to ignore temporary factors at the time a decision with future payoffs is taken. However, a growing body of literature on Projection Bias (Loewenstein, O'Donoghue, and Rabin [2003], Busse, Pope, Pope, and Silva-Risso [2014]) have formalized and found evidence that people are in fact influenced by transient states when making inter-temporal decisions.

I focus on transient weather fluctuations. Evidence from psychology suggests that days with high cloud cover induce worse moods. Hence, on a bad-weather day, individuals may feel more depressed than usual. If people are not fully able to account for the effect of weather, they may ask for (changes in) medications. I derive a model of a person considering treatment decisions and show that when projection bias is present, transient states might play a role. To test this prediction, I use detailed administrative medical records and daily county-level meteorological data in the United States from 01/01/2003 through 12/31/2004. Medical data come from the Truven Health MarketScan® database. Of the 12,094,219 enrollees, 13.60% filled at least one antidepressant prescription, and 7.86% had a diagnosis of a mental disease or disorder. Meteorological data are from the National Climatic Data Center (NCDC).

As a preliminary check, I test the effect of daily transient weather fluctuations on the percentage of appointments that involve a diagnosis of a mental disease or disorder. I find that the occurrence of snow is associated with a 0.13 percentage point decrease in the percentage of mental disease and disorder diagnosis, from a 1.93% baseline. Weather fluctuations in other dimensions do not seem to systematically lead to a change in the percentage of patients that are diagnosed with a mental disease or disorder. My specification includes county-year, day of the week, week of the year, year, and climatic region fixed effects. Climatic regions follow the classification of the National Centers for Environmental Information (Karl and Koss, 1984).

As a second preliminary analysis, I study the effect of transient weather on the daily total filling of antidepressants at the county level. The average number of antidepressants filled per county-day is 16.37. I find that snow (rain) leads a 1.08% (0.56%) decrease in the number of antidepressants filled. It is plausible, however, that the occurrence of rain and snow increase the costs associated with filling a prescription. Further, a one standard deviation (19.24°F) increase in temperature is found to lead to a 0.81% increase in the number of antidepressants filled.

My main analysis focuses on patient behavior during a small interval of time after they have been seen by a physician. I look at how weather influences antidepressant filling decision within a patient; I only include appointments that involved a major diagnosis of a mental disease or disorder. I find that a one standard deviation increase in the amount of cloud coverage (2.73 oktas) leads to a 0.063 percentage point increase in the probability that a patient fills an antidepressant prescription on appointment day. That is a 1.04% increase from the 6.07% baseline. The impact of cloud coverage fades with time. The effect is borderline significant within a day of the appointment, and insignificant within seven days. I also find small effects associated with snow, rain, and temperature.

I perform several heterogeneity analysis that build on the main analysis. Most most of the impact of cloud coverage on antidepressant filling is due to an increase on the number of new prescriptions, and not an increase in refills. I also present results separately for prescriptions filled in a pharmacy or via mail order. Virtually all the impact of weather variables on antidepressant filling happens at the pharmacy; I do not find that weather impacts the probability of filling antidepressants via mail order. Further, I show results per climatic region in the contiguous United States. Most regions have similar coefficients associated with cloud coverage, but only in the Northeast and Upper Midwest that coefficient is statistically significant. Perhaps not coincidentally, those are the two biggest regions in my data in terms of number of patients.

Additionally, I find that most of the impact of cloud coverage on the filling of antidepressants is led by patients who have had appointments during the Winter. A one (year-round) standard deviation increase in cloud coverage (2.73 oktas) lead to a 0.229 percentage point increase in the probability that a patient fills an antidepressant prescription in a pharmacy on the same day of the appointment, a 3.78% increase from the 5.54% (year-round) baseline. I also show results according to the dosing of a particular drug product. Most of the results seem to be led by filling of drugs of intermediate dosing. This is also the group of drus that is most frequently prescribed to patients in the data.

This paper relates to the literature that tests behavioral economics models using field data (see DellaVigna [2009] for a review). In specific, it contributes to the literature on Projection Bias as conceptualized by Loewenstein, O'Donoghue, and Rabin (2003). This paper closely relates to Busse, Pope, Pope, and Silva-Risso (2014), who investigate whether consumers are affected by weather when they purchase cars. They find that buying convertibles and four-wheel-drive cars is dependent on the weather at the time of purchase. Another related paper is Conlin, O'Donoghue, and Vogelsang (2007), find that purchases of cold-weather items are over-influenced by the weather at the time of purchase. Specifically, they find that purchases made in low temperatures are more likely to be returned.

The remaining of the paper is organized as follows. Section 2.3 introduces a theoretical framework and derives the main prediction of Projection Bias in this context. Section 2.3 describes the administrative data. Section 2.4 discusses the impact of weather on mental disease and disorder diagnosis. The impact of weather on antidepressant filling is discussed in section 2.5. Section 2.6 discusses the filling behavior of patients following an appointment. Finally, section 2.7 concludes.

2.2 Theoretical Framework

Consider a person deciding whether or not to initiate a treatment for depression.[1] Her time-varying mental health state s_t is formed by two components: structural well-being w, and transient mood m_t,

$$s_t = w + m_t. \tag{2.1}$$

The m_t component fluctuates on a daily basis, immediately affected by changes in mood-affecting variables, such as weather. The w component is not affected by transient shifts in mood.

In particular, I assume that m_t takes on two possible values, m^b and m^g, on bad and good weather days, respectively. Let $m_b < 0 < m_g$. I assume that a fixed proportion p_g of days have good weather, and $1 - p_g$ have bad weather. Let $w \in R$, with $w \geq 0$ corresponding to healthy structural well-being states and $w < 0$ corresponding to varying levels of depression.

[1] In reality, that decision will hopefully be taken with the support of a medical professional. I abstract from that for now.

At each day, the person has the choice of initiating a prescription drug treatment for depression. The treatment has an immediate cost of c and a per-period future net benefit of

$$b(d_t) = \begin{cases} -wd_t, & \text{if } w < 0 \\ 0, & \text{if } w \geq 0 \end{cases}, \tag{2.2}$$

where d_t indicates ongoing treatment for depression. This means that a currently depressed person reverts to $w = 0$ one period after treatment starts, and that a non-depressed person derives no benefit from treatment.

A standard-model person is able to discern between the transient and structural components. When making predictions for any future period, the best estimate of future well-being, given a current mental health state, can be expressed as

$$u(s_{t+\tau}, d_{t+\tau}|s_t) = w + p_g m_g + (1 - p_g)m_b + b(d_{t+\tau}). \tag{2.3}$$

She will initiate treatment if

$$-c + \sum_{\tau=1}^{\infty} \delta^\tau u(s_{t+\tau}, 1|s_t) > \sum_{\tau=1}^{\infty} \delta^\tau u(s_{t+\tau}, 0|s_t), \tag{2.4}$$

which results in $c < -\frac{\delta}{1-\delta}w$. The standard-model person will initiate treatment if she is in depression, $w < 0$, and if benefits outweigh costs. That decision is not influenced by the transient mood component m_t.

Consider now an individual that suffers from projection bias. She is not able to fully disentangle the part of her current mental health state that is due to structural factors and transient factors. As a consequence, when making predictions for future well-being, she believes transient moods will be permanent, at least partially,

$$\hat{u}(s_{t+\tau}, d_{t+\tau}|s_t) = (1 - \alpha)u(s_{t+\tau}, d_{t+\tau}|s_t) + \alpha u(s_t, d_{t+\tau}|s_t), \tag{2.5}$$

where $\alpha \in [0, 1]$ is the projection bias parameter. This nests the standard model with $\alpha = 0$. In the extreme case, $\alpha = 1$, the person will act as if her current mental health is entirely due to permanent structural factors.

Given the linearity of the model, another way to think of projection bias here is that the person believes her permanent mental health state is given by $(1 - \alpha)w + \alpha s_t(w + m_t) = w + \alpha m_t$ instead of w. As such, she estimates the benefits of the depression treatment by

$$\hat{b}(d_t) = \begin{cases} -w - \alpha m_t, & \text{if } w + \alpha m_t < 0 \\ 0, & \text{if } w + \alpha m_t \geq 0 \end{cases}. \tag{2.6}$$

For simplicity, I focus on the case $\alpha = 1$ in what follows.[2] Consider a person who is depressed, $w < 0$, on a bad weather day. She will initiate treatment if

[2] All cases $\alpha \in (0, 1]$ share the same qualitative results.

$$- c + \sum_{\tau=1}^{\infty} \delta^{\tau} \left(w + m^{b} + \hat{b} \right) > \sum_{\tau=1}^{\infty} \delta^{\tau} \left(w + m^{b} \right), \tag{2.7}$$

which is equivalent to $c < -\frac{\delta}{1-\delta}(w + m_b)$. The projection bias leads her to take the transient mood m_b into account. She will be more likely to initiate a treatment for depression on a bad weather day.

Other cases follow an analogous logic. A depressed individual on a good weather day with $w + m^g < 0$ will choose treatment if $c < -\frac{\delta}{1-\delta}(w + m_g)$. A depressed individual on a good weather day with $w + m^g > 0$ will not believe she is in depression and not start treatment. In the two last cases, good weather decreases the likelihood of treatment. A non-depressed individual on a bad weather day with $w + m^b < 0$ will act as if she is depressed and choose treatment if $c < -\frac{\delta}{1-\delta}(w + m_b)$; bad weather here leads to unnecessary treatment. A non-depressed individual on a bad weather day with $w + m^b > 0$ will not not initiate treatment. Finally, a non-depressed individual on a good weather day will have $w + m^b > 0$ and will not treat herself. To the extent that weather impact transient mood, an agent who displays projection bias will be more (less) likely to initiate treatment for depression on a bad (good) weather day. To the extent that weather does not immediately impact structural well-being, transient weather does not influence the standard-model agent depression treatment decisions.

Well-Being Considerations

Projection bias unambiguously hurts the well-being of an individual if it is the only deviation from standard behavior influencing the antidepressant treatment decision. As seen in the previous paragraphs, projection bias may lead an individual to initiate treatment in cases where it is not cost-effective or even in cases when the person is not depressed. It may also lead a person not to treat herself when treatment is advisable.

On the other hand, projection bias may in fact improve the well-being of an individual who is also present-biased. Treatment for depression is an activity with immediate costs and delayed benefits. As such, it is not implausible to expect that several people for whom treatment is recommended are not in treatment due to procrastination. If that is the case, the increased likelihood to initiate treatment in a bad weather day might in fact help.

2.3 Data

I use administrative individual-level medical data from the *Truven Health MarketScan® Research Databases*. Weather data come from the National Climatic Data Center (NCDC). The period of analysis is 01/01/2003 through 12/31/2004. Summary statistics are presented on Table 2.1.

Medical

Medical data come from MarketScan's Commercial Claims and Encounters segment, which includes active employees, early retirees, COBRA continues, and their dependents insured by employer-sponsored plans from approximately 45 large employers in the United States.

Data on the use of prescription drugs come from the Outpatient Pharmaceutical Claims table. Each record represents a drug claim at the pharmacy or via mail order. Each drug is uniquely identified by its National Drug Code (NDC), which assigns a different code for each drug product of a specific dosing produced by a specific manufacturer. Drugs can be grouped according to their therapeutic class based on the pharmacological category of the drug product. I restrict attention to drugs classified as *antidepressants*. Out of the 12,094,219 patients in the data, 1,645,183 (13.0%) have filled at least one antidepressant prescription in the period of analysis. Figure 2.2 depicts the ten most frequently filled antidepressants in the data, as a percentage of total antidepressants filled.

Data from medical appointments come from the Outpatient Services table, that contains encounters and claims for services that were rendered in a doctor's office, hospital outpatient facility, emergency room or other outpatient facility. Of particular interest are appointments in which the patient was diagnosed with a mental disease or disorder. The major diagnostic category *mental diseases and disorders* (MDC 19) includes acute adjustment reaction and psycho-social dysfunction, depressive neuroses, non-depressive neuroses, disorders of personality and impulse control, organic disturbances and mental retardation, psychoses, behavioral and developmental problems, and other mental diagnoses. Out of the 12,094,219 patients in the data, 950,048 (7.86%) have had an appointment with a mental disease or disorder diagnosis in the period of analysis. There are a total of 4,839,861 such appointments recorded in the data.[3]

I construct indicator variables for the filling behavior of a patient following a medical appointment in which there was a mental disease or disorder diagnosis. As per Table 2.1, 6.46% (15.66%) of such medical appointments were followed by the filling of an antidepressant on the same day (within seven days). Enrollment records, demographic characteristics, and geographic locations come from the Enrollment table. All tables are linked via unique individual identifiers.

Weather

Weather data come from the National Climatic Data Center (NCDC); cloud coverage from the Integrated Surface Data (ISD) dataset, all other variables from the Global Summary of the Day (GSOD) dataset. I exclude data from stations with missing latitude, longitude, or elevation data, stations that started operating on or after 01/01/2002 or finished operating

[3] The last two statistics do not include appointments with medical professionals who are not able to prescribe drugs.

on or before 01/01/2005. I further excludes stations with an altitude exceeding that of the lowest laying station in the county in more than 500 meters and stations located in a body of water. Figure 2.2a depicts all 2,523 meteorological stations in the contiguous United States that are included in the analysis.

Weather data is linked to medical data using county identifiers. A county is included in the analysis if it contains at least one meteorological station in its territory. If two or more stations are located in the same county, I use the county-average of each weather variable weighting station-level data based on the number of daily observations recorded. That results in 972 counties. Summary statistics are presented on the Panel A of Table 2.1. The grouping of states into climatic regions follows the classification of the National Centers for Environmental Information (Karl and Koss, 1984) as per Figure 2.6. I use weather at the county of residence of an enrollee, as opposed to that of the employer, pharmacy, or medical service provider.

2.4 Mental Disease and Disorder Diagnosis

I model the percentage of appointments in county c on day t that involve a diagnosis of a mental disease or disorder as

$$PctMentalDiagnosis_{ct} = \alpha_1 Weather_{ct} + \alpha_2 DoW_t + \alpha_3 Region_c Week_t + \xi_c Year_t + u_{ct} \quad (2.8)$$

where $Weather_{ct}$ includes temperature, cloud coverage, dew point, visibility, wind speed, as well as indicators for rain, snow, and fog. DoW_t, $Week_t$, $Year_t$, and $Region_c$ are day of the week, week of the year, year, and climatic region indicators. Climatic regions follow the classification of the National Centers for Environmental Information (Karl and Koss, 1984) as per Figure 2.6. I include an interaction of county fixed effects, ξ_c, and the year indicator. Standard errors are clustered at the climatic region level.

Table 2.2 presents the results of the specification in 2.8. The occurrence of snow is associated with a 0.13 percentage point decrease in the percentage of mental disease and disorder diagnosis, from a 1.93% baseline. Weather fluctuations in other dimensions do not seem to systematically lead to a change in the percentage of patients that are diagnosed with a mental disease or disorder.

2.5 Antidepressant Filling

Let $TotalFillings_{ct}$ denote the total number of antidepressants filled in county c at day t

$$TotalFillings_{ct} = \eta Weather_{ct} + \alpha_1 Dow_t + \alpha_2 Region_c \times Week_t + \xi_c \times Year_t + \beta \mathrm{X}_{it} + u_{ct} \quad (2.9)$$

where $Weather_{ct}$ includes temperature, cloud coverage, dew point, visibility, wind speed, as well as indicators for rain, snow, and fog. DoW_t, $Week_t$, $Year_t$, and $Region_c$ are day of the week, week of the year, year, and climatic region indicators. Climatic regions follow the classification of the National Centers for Environmental Information (Karl and Koss, 1984) as per Figure 2.6. I include an interaction of county fixed effects, ξ_c, and the year indicator. Standard errors are clustered at the climatic region level.

Table 2.2 presents the results of the specification in 2.8. The result on column four indicates that snow, rain, and changes in temperature lead to changes in the total number of antidepressants filled. It is plausible that the occurrence of rain and snow increase the costs associated with filling a prescription. In fact, I find that snow (rain) leads a 1.08% (0.56%) decrease in the number of antidepressants filled. The average number of antidepressants filled per county-day is 16.37. Summary statistics for rain and snow are displayed on Table 2.1. As per temperature, a change in one standard deviation (19.24°F) is found to lead to a 0.81% increase in the number of antidepressants filled.

Columns 5 and 6 of Table 2.2 show the results of specification 2.8 separately for refills and new prescriptions.

2.6 Antidepressant Filling After Appointment

I model the filling behavior of a patient following an appointment in which there was a mental disease or disorder diagnosis as

$$FillsAntidepressant_{it} = \eta Weather_{ct} + \alpha_1 Dow_t + \alpha_2 Region_c \times Week_t + \beta \mathrm{X}_{it} + \xi_i + u_{it} \quad (2.10)$$

where $FillsAntidepressant_{it}$ equals one if the patient fills an antidepressant prescription within a specific amount of time following the appointment. Different time windows will be used. $Weather_{ct}$ includes temperature, cloud coverage, dew point, visibility, wind speed, as well as indicators for rain, snow, and fog. DoW_t, $Week_t$, $Year_t$, and $Region_c$ are day of the week, week of the year, year, and climatic region indicators. Patient characteristics X_{it} includes age, gender, employee classification, employment status, and relation to the employee. Climatic regions follow the classification of the National Centers for Environmental Information (Karl and Koss, 1984) as per Figure 2.6. I include an interaction of county fixed effects, ξ_c, and the year indicator. Standard errors are clustered at the climatic region level. Patients who move across county lines in the period of study are not included in the analysis.

The results of specification 2.10 are presented on Table 2.4. I find that a one standard deviation increase in the amount of cloud coverage (2.73 oktas) lead to a 0.063 percentage point increase in the probability that a patient fills an antidepressant prescription on very same day they were seen by a doctor and diagnosed with a mental disease or disorder. That represents a 1.04% increase from the baseline 6.07% of patients who typically fill a prescription in such circumstances. Columns 5 and 7 of Table 2.4 show that the impact of cloud-coverage at the time of the appointment on filling behavior fades with time. The proportion of patients who fill an antidepressant prescription is borderline significant within a day of the appointment, and insignificant within seven days. No other weather variable is found to influence filling behavior.

Heterogeneity of the Results

The results on Table 2.5 show that most of the impact of cloud coverage on the filling of antidepressant prescriptions is mostly due to an increase in the number of new prescriptions, and not an increase in refills. In addition, I find that the estimates associated with rain and snow are related to the proportion of patients who fill a new antidepressant prescription on appointment day. By its turn, an increase in temperature is found to lead to a decrease in refills of antidepressants following an appointment. The magnitude of these three last results is small, however.

On Table 2.6 I presents results separately for prescriptions filled in a pharmacy or via mail order. I find that a one standard variation increase in the amount of cloud coverage (2.73 oktas) lead to a 0.052 percentage point increase in the probability that a patient fills an antidepressant prescription in a pharmacy on the same day of the appointment, a 0.94% increase from the 5.54% baseline. Still focusing on filling at the pharmacy, I find that the occurrence of snow leads to a 0.131 percentage point decrease in the filling of antidepressant. I do not find that weather impacts the probability of filling antidepressants via mail order. These results must be taken with a grain of salt, however, as the vast majority of prescriptions in the data are filled at a pharmacy.

Table 2.7 show results for each climatic region in the contiguous United States. Climatic regions follow the classification of the National Centers for Environmental Information (Karl and Koss, 1984) as per Figure 2.6. I exclude regions that do not represent at least 2% of the total patients in the data (Northern Rockies, Southwest, and West). While all regions, except the Southeast, have similar coefficients associated with cloud coverage, the only two regions with statistically significant results on that variable are the Northeast and Upper Midwest. Not coincidentally, perhaps, those are the two biggest regions in my data in terms of number of patients.

On Table 2.8 I present results for each one of the four seasons of the year. I find that most of the positive impact of cloud coverage on the filling of antidepressants is led by patients who have had appointments during Winter. A one (year-round) standard deviation increase in cloud coverage (2.73 oktas) lead to a 0.229 percentage point increase in the probability that a patient fills an antidepressant prescription in a pharmacy on the same day of the appointment, a 3.78% increase from the 5.54% (year-round) baseline.

Finally, Table 2.9 shows results according to the dosing of a particular drug product. Consider a drug product that is available in four different doses: 10mg, 20mg, 50mg, and 100mg. Each dosing is a different drug according to the NDC. I arbitrarily assign drugs to three mutually exclusive groups: minimum dose, intermediate, and maximum dose. In the case of the hypothetical drug product in question, the 10mg version is assigned to the minimum dose group, the 100mg version to the maximum dose group, and the 20mg and 50mg versions to the intermediate group. Not surprisingly, most of the results seem to be led by filling of drugs of intermediate dosing. This is also the group of drugs that is most frequently prescribed to patients in the data.

2.7 Discussion

There are several distinct antidepressant regimens currently available, and a usual treatment involves some experimentation with different prescription drugs. During an appointment, a patient is typically asked about the symptoms of her depression, and a decision is taken about whether or not to initiate or change a treatment with antidepressants. Temporary factors, such as weather, may influence the answer given by the patient to the doctor, consequently influencing medication choice. I derive a model of a person considering treatment decisions and show that when projection bias is present, weather might play a role in treatment choices. I use detailed administrative medical records and daily county-level meteorological data in the United States from 01/01/2003 through 12/31/2004. Medical data come from the Truven Health MarketScan® database. Meteorological data are from the National Climatic Data Center.

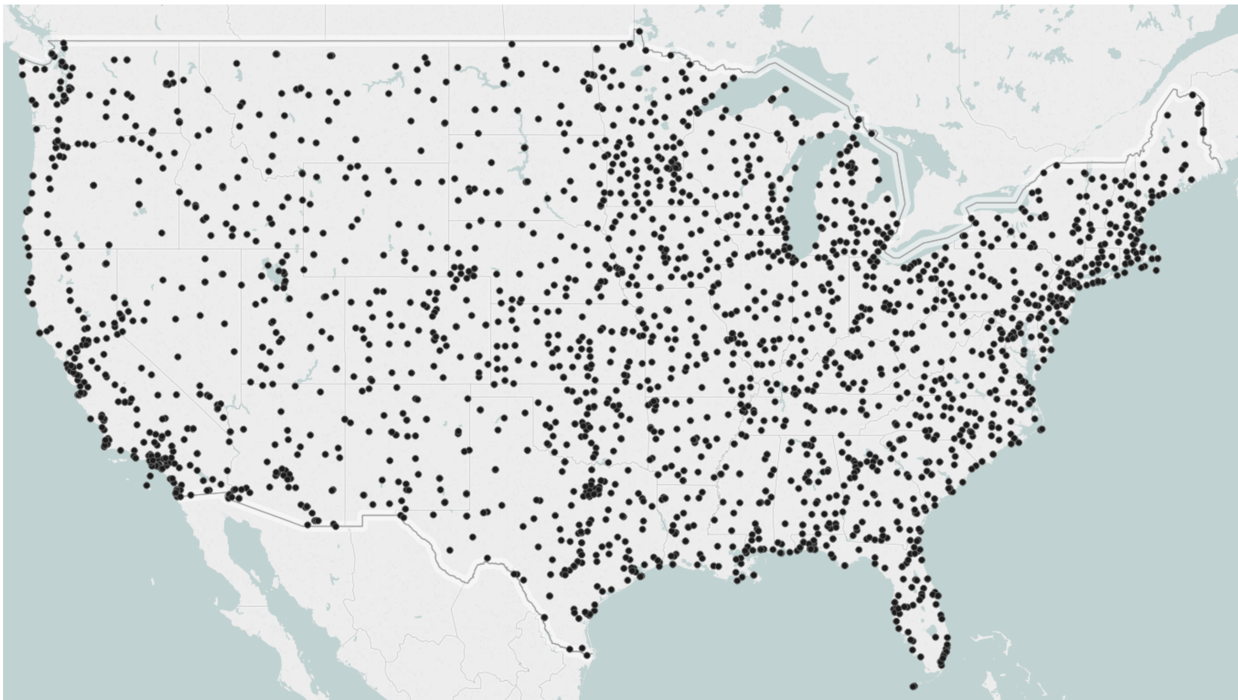
My main analysis focuses on patient behavior during a small interval of time after they have been seen by a physician. I look at how weather influences antidepressant filling decision within a patient; I only include appointments that involved a major diagnosis of a mental disease or disorder. My specification includes county-year, day of the week, week of the year, year, and climatic region fixed effects. Climatic regions follow the classification of the National Centers for Environmental Information (Karl and Koss, 1984). I find that a one standard deviation increase in the amount of cloud coverage (2.73 oktas) leads to a 0.063 percentage point increase in the probability that a patient fills an antidepressant prescription on appointment day. That is a 1.04% increase from the 6.07% baseline. The impact of cloud coverage fades with time. The effect is borderline significant within a day of the appointment, and insignificant within seven days. I also find small effects associated with snow, rain, and temperature.

I perform several heterogeneity analysis that build on the main analysis. Most most of the impact of cloud coverage on antidepressant filling is due to an increase on the number of new prescriptions, and not an increase in refills. I also present results separately for prescriptions filled in a pharmacy or via mail order. Virtually all the impact of weather variables on antidepressant filling happens at the pharmacy; I do not find that weather impacts the probability of filling antidepressants via mail order. Further, I show results per climatic region in the contiguous United States. Most regions have similar coefficients associated with cloud coverage, but only in the only in the Northeast and Upper Midwest that coefficient is statistically significant. Perhaps not coincidentally, those are the two biggest regions in my data in terms of number of patients. Additionally, I find that most of the impact of cloud coverage on the filling of antidepressants is led by patients who have had appointments during the Winter. A one (year-round) standard deviation increase in cloud coverage (2.73 oktas) lead to a 0.229 percentage point increase in the probability that a patient fills an antidepressant prescription in a pharmacy on the same day of the appointment, a 3.78% increase from the 5.54% (year-round) baseline. I also show results according to the dosing of a particular drug product. Most of the results seem to be led by filling of drugs of intermediate dosing. This is also the group of drugs that is most frequently prescribed to patients in the data.

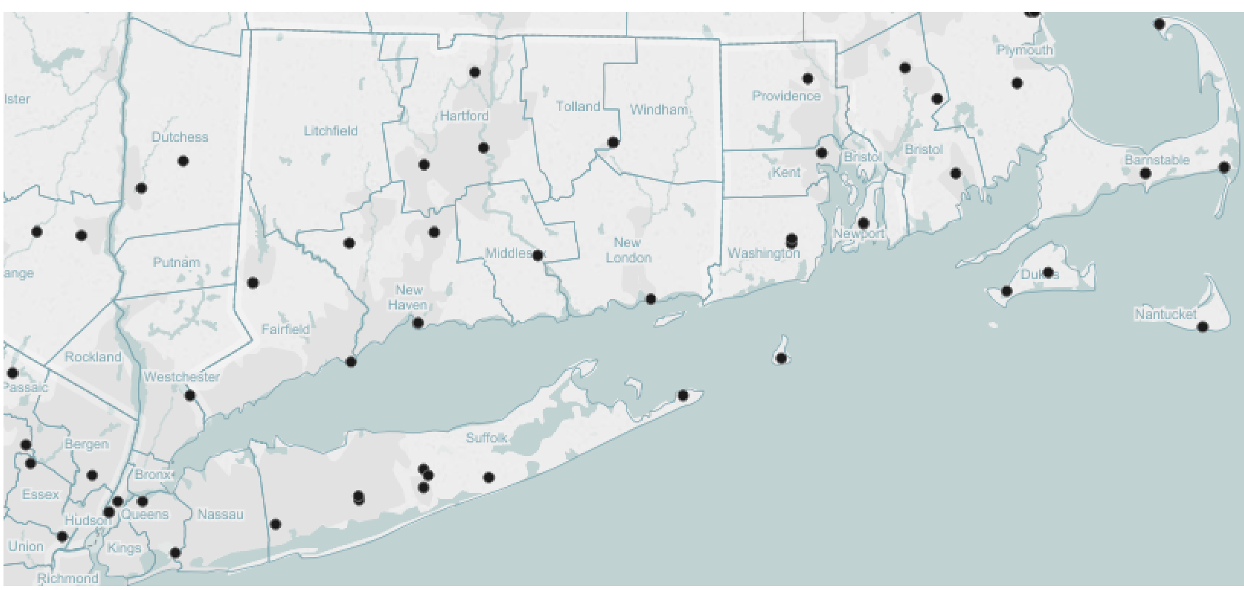
Projection bias unambiguously hurts the well-being of an individual if it is the only deviation from the standard model influencing the antidepressant treatment decision. It may lead an individual to initiate treatment in cases where it is not cost-effective or even in cases when the person is not depressed. It may also lead a person not to treat herself when treatment would be advisable. On the other hand, projection bias may improve the well-being of an individual who is also present-biased. Treatment for depression is an activity with immediate costs and delayed benefits. It is not implausible to expect that several people for whom treatment for depression is advisable and cost-effective are not currently in treatment due to procrastination. If that is the case, the increased likelihood to initiate treatment in a bad weather day might in fact help.

Figure 2.1: Meteorological Stations

(a) Stations in the Contiguous United States

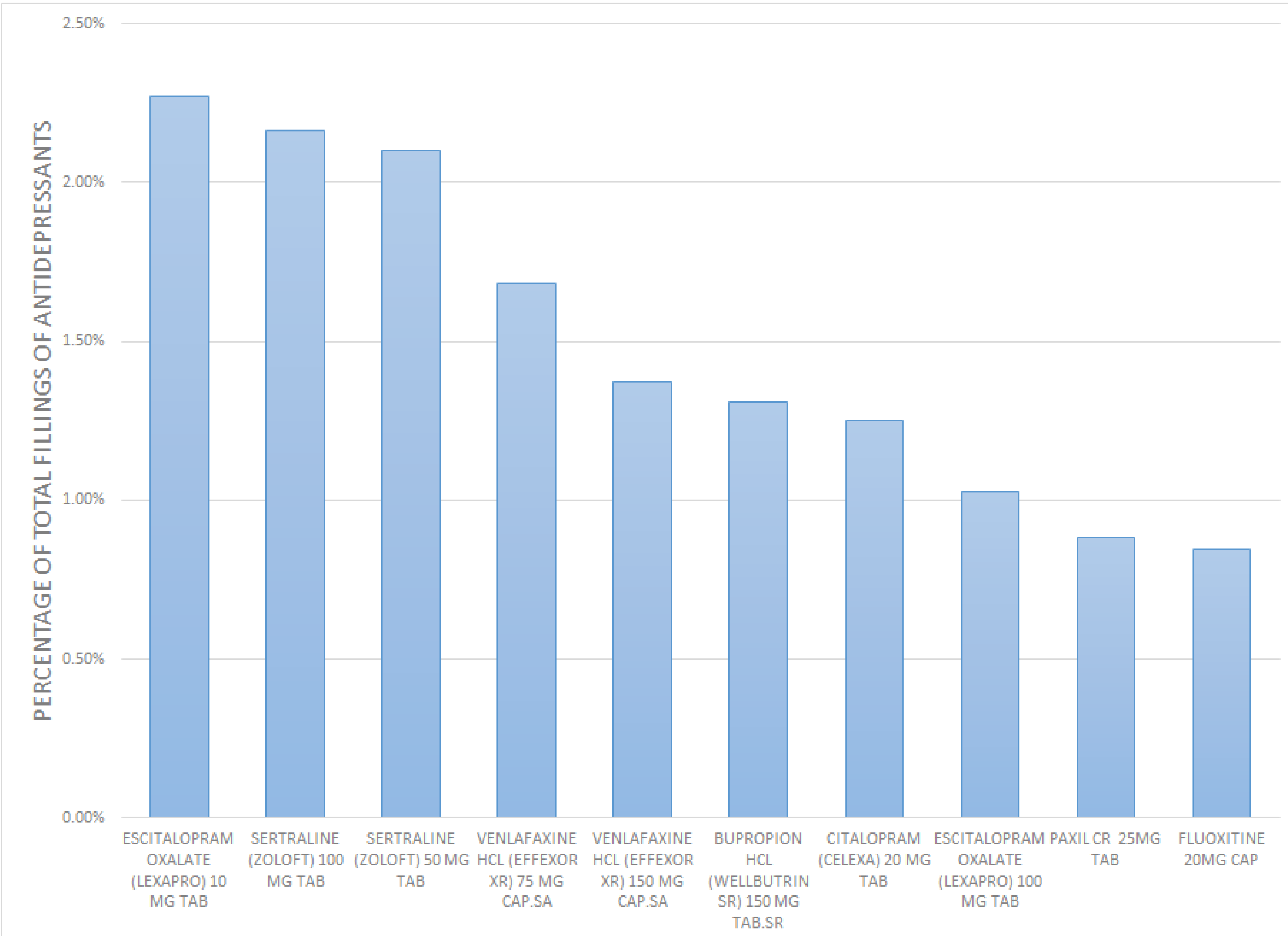


(b) Stations in Northeast Region Counties (detail, partial)



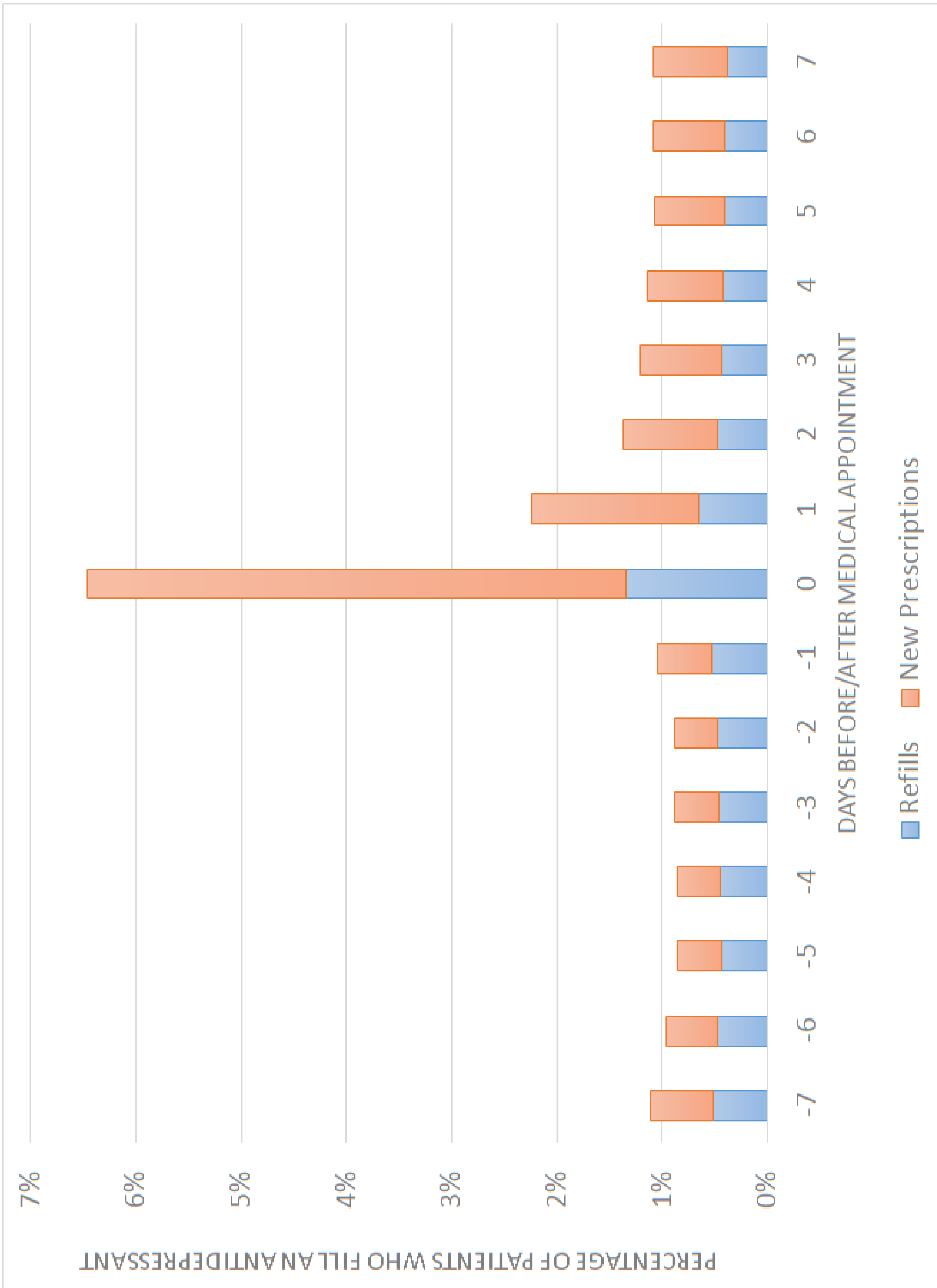
Notes: The figures depicts the location of a subset of the meterological stations available at the National Climatic Data Center (NCDC). Excludes stations with missing latitude, longitude, or elevation data. Excludes stations that started operating on or after 01/01/2002 or finished operating on or before 01/01/2005. Excludes stations with an altitude exceeding that of the lowest laying station in the county in more than 500 meters. Excludes stations located in a body of water.

Figure 2.2: Antidepressants Most Commonly Filled



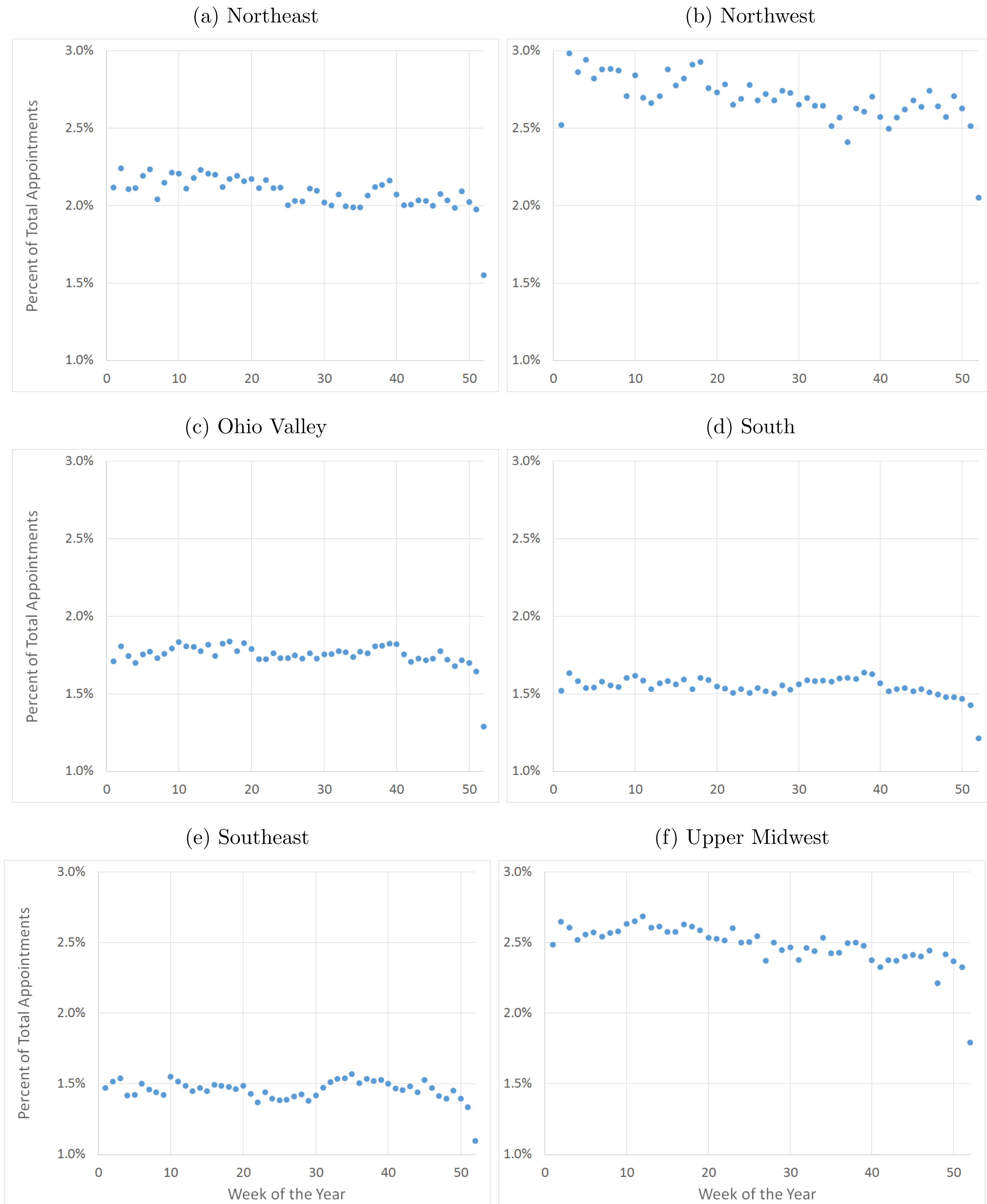
Notes: The figure depicts the ten most frequently filled antidepressants in the data, as a percentage of total antidepressants filled. Each drug is uniquely identified by its National Drug Code (NDC), which assigns a different code for each drug product of a specific dosing produced by a specific manunfacturer. The period is 01/01/2003-12/31/2004.

Figure 2.3: Antidepressants Most Commonly Filled



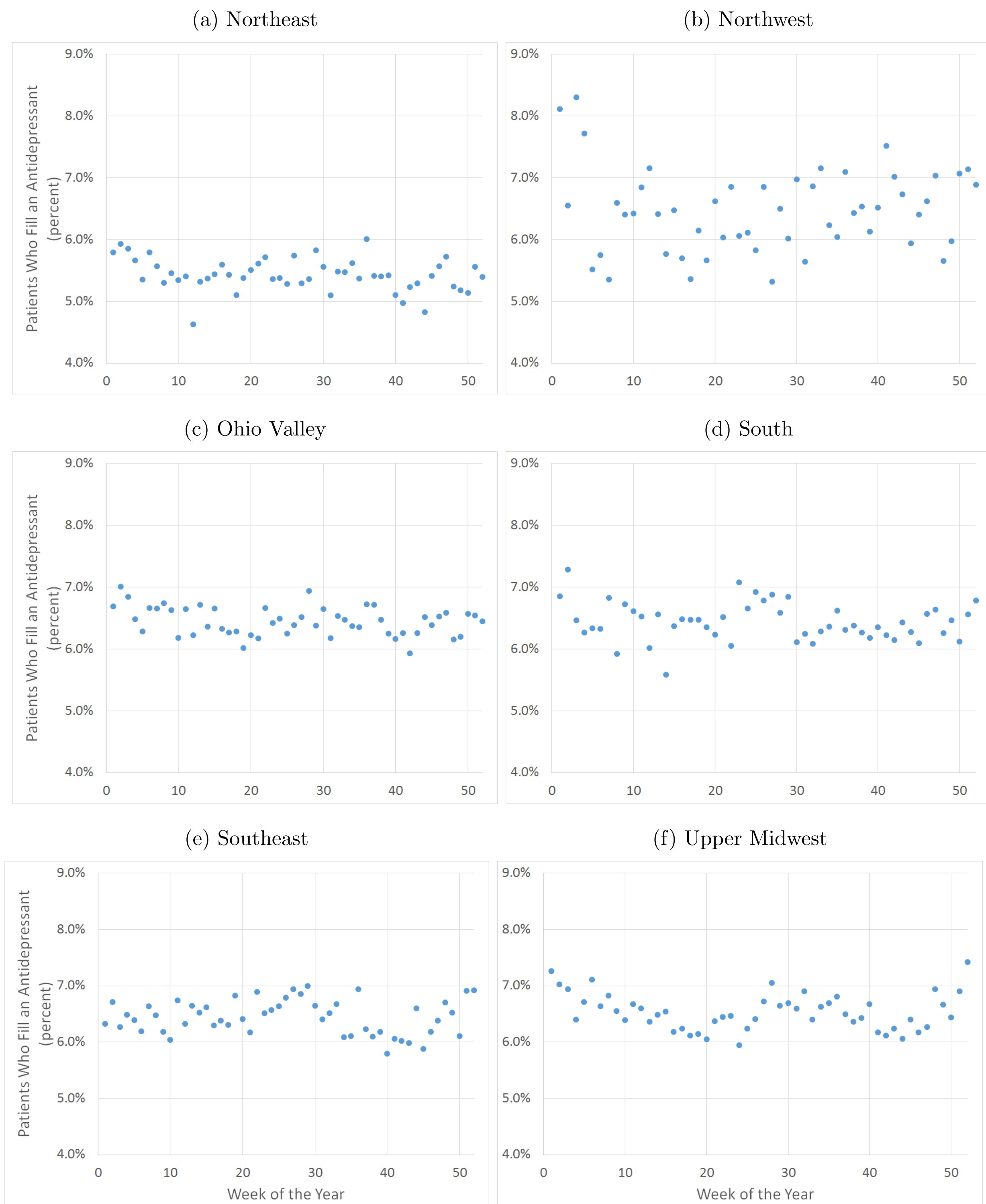
Notes: The figure depicts the percentage of patients who fill an antidepressant prescription during a fifteen-day window period around appointment day. Only includes outpatient appointments with a medical professional who is able to prescribe drugs. Only includes appointments in which the major diagnosis is that of a mental disease or disorder. Outpatient prescription drug data from the MarketScan Commercial Claims & Encounters Research Databases. The period is 01/01/2003-12/31/2004.

Figure 2.4: Appointments with a Mental Disease or Disorder Diagnosis, by Week of the Year



Notes: The figure depicts the percentage of total appointments in which the major diagnosis is a mental disease or disorder. Only includes outpatient appointments with a medical professional who is able to prescribe drugs. Climatic regions follow the classification of the National Centers for Environmental Information (Karl and Koss, 1984). The period is 01/01/2003-12/31/2004.

Figure 2.5: Enrollees Filling of Antidepressants on Appointment Day, by Week of the Year



Notes: The figure depicts the percentage of patients who fill an antidepressant prescription on appointment day. Only includes outpatient appointments with a medical professional who is able to prescribe drugs. Only includes appointments in which the major diagnosis is that of a mental disease or disorder. Climatic regions follow the classification of the National Centers for Environmental Information (Karl and Koss, 1984). The period is 01/01/2003-12/31/2004.

Table 2.1: Descriptive Statistics

A - Daily County-Level Weather Data

	Mean	*SD*
Temperature (Fahrenheit)	54.19	19.24
Cloud Coverage (oktas)	3.40	2.73
Dew Point (Fahrenheit)	43.15	19.42
Visibility (miles)	8.92	2.70
Wind Speed (knots)	6.55	3.25
Rain Indicator	0.29	
Snow Indicator	0.08	
Fog Indicator	0.21	

C - Totals

	Total	*% of total*
Meterological Stations	2,523	
Counties	972	
Enrollees	12,094,219	
at least one antidepressant filled	1,645,183	13.60
at least one psych. appointment	950,048	7.86
Psych. appointments	4,839,861	
antidepressant filled same day	312,802	6.46
antidepressant filled in one day	420,927	8.69
antidepressant filled in seven days	757,941	15.66

B - Patient Demographics

At least one psych. appointment	*Mean*	*SD*	*% of total*
Age	35.70	17.31	
Female Indicator	0.57		
Relation to Employer:			
Employee			46.09
Spouse			24.39
Child/Other			29.51
Climatic Regions			
Northeast (NE)			19.60
Northwest (NW)			4.98
Ohio Valley (OV)			19.98
South (S)			18.34
Southeast (SE)			15.34
Upper Midwest (UM)			19.30
Others			2.46

Notes: The period is 01/01/2003-12/31/2004. Psych. appointment here refers to an outpatient appointment with any medical professional able to prescribe drugs in which the major diagnosis is a mental disease or disorder. Weather data from the National Climatic Data Center (NCDC); cloud coverage from the Integrated Surface Data (ISD) dataset, all other variables from the Global Summary of the Day (GSOD) dataset. Outpatient services and prescription drug data from the MarketScan Commercial Claims & Encounters Research Databases.

Table 2.2: Effect of Weather on Mental Disease and Disorder (MDD) Diagnosis

Percentage of Appointments with MDD Diagnosis	(1)	(2)	(3)	(4)
Temperature (Fahrenheit)	3.12e-05	2.90e-05	9.63e-06	1.19e-05
	(2.37e-05)	(2.35e-05)	(2.81e-05)	(3.22e-05)
Cloud Coverage (oktas)	6.49e-05**	6.91e-05**	4.79e-05	6.55e-05
	(2.80e-05)	(2.87e-05)	(3.51e-05)	(3.69e-05)
Rain Indicator	4.78e-05	-3.04e-05	-4.81e-05	-5.26e-05
	(0.000234)	(0.000260)	(0.000276)	(0.000315)
Snow Indicator	-0.00103**	-0.00102**	-0.00105***	-0.00134***
	(0.000361)	(0.000369)	(0.000273)	(0.000296)
Fog Indicator	4.26e-05	9.94e-06	-2.85e-05	-3.97e-05
	(0.000197)	(0.000186)	(0.000191)	(0.000196)
Dew Point (Fahrenheit)	-2.37e-05	-2.22e-05	1.23e-06	-1.63e-06
	(2.32e-05)	(2.37e-05)	(2.58e-05)	(2.87e-05)
Visibility (miles)	-2.55e-05	-1.80e-05	3.29e-06	9.40e-06
	(6.21e-05)	(6.58e-05)	(6.70e-05)	(7.31e-05)
Wind Speed (knots)	5.70e-05	5.57e-05	4.63e-05	4.56e-05
	(4.09e-05)	(3.81e-05)	(4.28e-05)	(4.49e-05)
County FE X Year FE	X	X	X	X
Day of the Week FE		X	X	X
Week of the Year FE			X	X
X Region FE				X
Mean dependent variable	0.019	0.019	0.019	0.019
Observations	489,511	489,511	489,511	489,511
R-squared	0.000	0.002	0.002	0.003
Number of County-Years	1,661	1,661	1,661	1,661

Notes: Each observation is measured at the county-day level. The period is 01/01/2003-12/31/2004. The dependent variable is the percentage of appointments with a mental disease or disorder diagnosis. Only includes outpatient appointments with a medical professional who is able to prescribe drugs. Standard errors clustered at the climatic region level. Climatic regions follow the classification of the National Centers for Environmental Information (Karl and Koss, 1984) as per Figure 2.6.

Table 2.3: Effect of Weather on Antidepressant Fillings

	All Prescriptions				Refills	New Presc.
Log Total Antidep. Filled	(1)	(2)	(3)	(4)	(5)	(6)
Temperature (Fahrenheit)	0.000261	-0.000270	0.000201	0.000426*	0.000138	0.000408
	(0.000450)	(0.000212)	(0.000135)	(0.000194)	(0.000272)	(0.000228)
Cloud Coverage (oktas)	0.00156	0.00124	0.000800	0.000709	0.00118*	0.000182
	(0.000860)	(0.000713)	(0.000695)	(0.000737)	(0.000600)	(0.000348)
Rain Indicator	-0.000926	-0.00609**	-0.00543*	-0.00563*	-0.00763***	-0.00242
	(0.00405)	(0.00258)	(0.00268)	(0.00248)	(0.00154)	(0.00392)
Snow Indicator	-0.00915	-0.0109***	-0.00564**	-0.0108***	-0.0101***	-0.0102***
	(0.00520)	(0.00216)	(0.00194)	(0.00279)	(0.00271)	(0.00201)
Fog Indicator	-0.00164	-0.00264	-0.00371	-0.00338	-0.000525	-0.00640***
	(0.00364)	(0.00244)	(0.00262)	(0.00292)	(0.00337)	(0.00120)
Dew Point (Fahrenheit)	-0.000742	-0.000256	-0.000195	-0.000201	-8.57e-05	-0.000173
	(0.000447)	(0.000242)	(0.000209)	(0.000224)	(0.000265)	(0.000257)
Visibility (miles)	-0.00136	0.000376	0.00108	0.00144	0.00160	0.00255**
	(0.00122)	(0.000923)	(0.000961)	(0.00106)	(0.000923)	(0.00109)
Wind Speed (knots)	-0.00101	-0.00114	-0.00101	-0.00105	-0.000933	-0.000759
	(0.00118)	(0.000983)	(0.000881)	(0.000895)	(0.000740)	(0.000717)
County FE X Year FE	X	X	X	X	X	X
Day of the Week FE		X	X	X	X	X
Week of the Year FE			X	X	X	X
X Region FE				X	X	X
Average Fillings, County-Day	16.317	16.317	16.317	16.317	10.653	8.583
Observations	391,097	391,097	391,097	391,097	356,837	300,577
R-squared	0.000	0.288	0.291	0.292	0.166	0.342
Number of County-Years	1,634	1,634	1,634	1,634	1,625	1,627

Notes: Each observation is measured at the county-day level. The dependent variable is the log of the total number of antidepressants filled. The period is 01/01/2003-12/31/2004. Standard errors clustered at the climatic region level. Climatic regions follow the classification of the National Centers for Environmental Information (Karl and Koss, 1984) as per Figure 2.6.

Table 2.4: Antidepressant Filling Following Appointment Day

	On Appointment Day				Within 1 Day	Within 7 Days
Fills Antidep. Indicator	(1)	(2)	(3)	(4)	(5)	(6)
Temperature (Fahrenheit)	-9.69e-06	2.77e-06	-5.52e-06	-4.50e-05	-4.66e-05	2.27e-05
	(6.03e-05)	(5.98e-05)	(6.14e-05)	(6.45e-05)	(8.51e-05)	(0.000124)
Cloud Coverage (oktas)	0.000206*	0.000212**	0.000205*	0.000231***	0.000167*	0.000195
	(9.16e-05)	(8.45e-05)	(8.97e-05)	(3.96e-05)	(8.41e-05)	(0.000140)
Rain Indicator	-8.46e-05	9.41e-05	6.65e-05	8.93e-05	0.000189	0.00109
	(0.000308)	(0.000277)	(0.000288)	(0.000287)	(0.000410)	(0.000914)
Snow Indicator	-0.000195	-0.000586	-0.000685	-0.00136**	-0.00143	-0.00125
	(0.000904)	(0.000782)	(0.000794)	(0.000534)	(0.000937)	(0.00104)
Fog Indicator	0.000545	0.000512	0.000512	0.000206	-0.000160	-0.000629
	(0.000383)	(0.000398)	(0.000407)	(0.000471)	(0.000617)	(0.000581)
Dew Point (Fahrenheit)	-1.82e-05	-2.79e-05	-2.17e-05	-2.30e-05	-1.93e-05	-0.000108
	(4.53e-05)	(4.50e-05)	(4.68e-05)	(5.34e-05)	(8.23e-05)	(0.000111)
Visibility (miles)	9.39e-05	0.000136	0.000132	0.000158	9.07e-05	6.20e-05
	(0.000116)	(0.000115)	(0.000120)	(0.000103)	(0.000127)	(0.000231)
Wind Speed (knots)	-5.60e-05	-5.95e-05	-5.77e-05	1.39e-05	8.13e-05	0.000119
	(7.12e-05)	(7.36e-05)	(7.35e-05)	(6.74e-05)	(5.27e-05)	(6.54e-05)
County FE X Year FE	X	X	X			
Day of the Week FE	X	X	X	X	X	X
Week of the Year FE	X	X	X	X	X	X
X Region FE		X	X	X	X	X
Patient Characteristics			X			
Patient FE				X	X	X
Mean Dependent Variable	0.0607	0.0607	0.0607	0.0607	0.0869	0.155
Observations	2,500,891	2,500,891	2,500,891	2,500,891	2,500,891	2,500,891
R-squared	0.001	0.001	0.006	0.001	0.001	0.001
Number of Patients	483,333	483,333	483,333	483,333	483,333	483,333

Notes: Medical data at the patient-day level. Weather data at the county-day level. Period is 01/01/2003-12/31/2004. The dependent variable is an indicator for filling an antidepressant prescription following an appointment. Only includes outpatient appointments with a medical professional who is able to prescribe drugs. Only includes appointments in which the major diagnosis is that of a mental disease or disorder. Enrollee characteristics include age, gender, employee classification, employment status, and relation to the employee. Standard errors clustered at the climatic region level. Climatic regions follow the classification of the National Centers for Environmental Information (Karl and Koss, 1984) as per Figure 2.6.

Table 2.5: Antidepressant Filling on Appointment Day, by Type of Prescription

	Refills		New Prescription	
Fills Antidepressant Indicator	(1)	(2)	(3)	(4)
Temperature (Fahrenheit)	-2.16e-05	-3.42e-05**	2.62e-05	-1.20e-05
	(1.21e-05)	(1.04e-05)	(4.46e-05)	(6.12e-05)
Cloud Coverage (oktas)	5.49e-05	3.33e-05	0.000169*	0.000214***
	(2.98e-05)	(3.83e-05)	(8.80e-05)	(5.86e-05)
Rain Indicator	-0.000144	-0.000246	0.000384	0.000491***
	(0.000141)	(0.000187)	(0.000216)	(0.000124)
Snow Indicator	-8.30e-05	-0.000264	-0.000952	-0.00137**
	(0.000191)	(0.000270)	(0.000624)	(0.000435)
Fog Indicator	0.000440**	0.000251	-0.000284	-0.000332
	(0.000165)	(0.000261)	(0.000397)	(0.000567)
Dew Point (Fahrenheit)	8.07e-06	2.24e-05	-3.03e-05	-3.88e-05
	(1.30e-05)	(1.45e-05)	(3.95e-05)	(4.84e-05)
Visibility (miles)	9.82e-05**	0.000131**	7.65e-05	5.79e-05
	(3.70e-05)	(5.00e-05)	(0.000119)	(0.000133)
Wind Speed (knots)	-4.69e-06	2.28e-05**	-5.69e-07	4.41e-05
	(1.21e-05)	(9.00e-06)	(5.79e-05)	(5.25e-05)
County FE X Year FE	X		X	
Day of the Week FE	X	X	X	X
Week of the Year FE X Region FE	X	X	X	X
Patient Characteristics	X		X	
Patient FE		X		X
Mean dependent variable	0.006	0.006	0.050	0.050
Observations	2,500,891	2,500,891	2,500,891	2,500,891
R-squared	0.002	0.000	0.005	0.001
Number of County-Years	1,595	1,595	1,595	1,595
Number of Patients	483,333	483,333	483,333	483,333

Notes: Medical data at the patient-day level. Weather data at the county-day level. Period is 01/01/2003-12/31/2004. The dependent variable is an indicator for filling antidepressant prescription on the day of the appointment. Only includes outpatient appointments with a medical professional who is able to prescribe drugs. Only includes appointments in which the major diagnosis is that of a mental disease or disorder. Enrollee characteristics include age, gender, employee classification, employment status, and relation to the employee. Standard errors clustered at the climatic region level. Climatic regions follow the classification of the National Centers for Environmental Information (Karl and Koss, 1984) as per Figure 2.6.

Table 2.6: Antidepressant Filling on Appointment Day, by Fulfillment Method

	In Pharmacy		By Mail	
Fills Antidepressant Indicator	(1)	(2)	(3)	(4)
Temperature (Fahrenheit)	-5.18e-06	-4.92e-05	-7.83e-06	-2.38e-06
	(5.84e-05)	(6.46e-05)	(8.04e-06)	(9.82e-06)
Cloud Coverage (oktas)	0.000201**	0.000191***	-8.75e-07	1.67e-05
	(7.84e-05)	(3.82e-05)	(1.65e-05)	(1.70e-05)
Rain Indicator	-2.27e-05	5.37e-05	6.63e-05*	6.24e-05
	(0.000294)	(0.000305)	(2.92e-05)	(3.41e-05)
Snow Indicator	-0.000601	-0.00131*	-6.99e-05	-0.000191
	(0.000844)	(0.000665)	(0.000113)	(0.000165)
Fog Indicator	0.000393	0.000191	3.83e-05	7.80e-05
	(0.000355)	(0.000387)	(6.56e-05)	(0.000119)
Dew Point (Fahrenheit)	-1.02e-05	-9.81e-06	-3.67e-06	-7.72e-06
	(4.55e-05)	(5.26e-05)	(9.89e-06)	(8.77e-06)
Visibility (miles)	0.000148	0.000108	-3.78e-06	2.25e-05
	(9.86e-05)	(9.28e-05)	(3.75e-05)	(3.08e-05)
Wind Speed (knots)	-5.92e-05	2.58e-05	5.75e-06	-9.08e-06
	(6.82e-05)	(7.47e-05)	(1.00e-05)	(1.45e-05)
County FE X Year FE	X		X	
Day of the Week FE	X	X	X	X
Week of the Year FE X Region FE	X	X	X	X
Patient Characteristics	X		X	
Patient FE		X		X
Mean dependent variable	0.0554	0.0554	0.0022	0.0022
Observations	2,500,891	2,500,891	2,500,891	2,500,891
R-squared	0.005	0.001	0.001	0.000
Number of County-Years	1,595	1,595	1,595	1,595
Number of Patients	483,333	483,333	483,333	483,333

Notes: Medical data at the patient-day level. Weather data at the county-day level. Period is 01/01/2003-12/31/2004. The dependent variable is an indicator for filling antidepressant prescription on the day of the appointment. Only includes outpatient appointments with a medical professional who is able to prescribe drugs. Only includes appointments in which the major diagnosis is that of a mental disease or disorder. Enrollee characteristics include age, gender, employee classification, employment status, and relation to the employee. Standard errors clustered at the climatic region level. Climatic regions follow the classification of the National Centers for Environmental Information (Karl and Koss, 1984) as per Figure 2.6.

Table 2.7: Antidepressant Filling on Appointment Day, by Climatic Region

	NE	NW	OV	S	SE	UM
Fills Antidepressant Indicator	(1)	(2)	(3)	(4)	(5)	(6)
Temperature (Fahrenheit)	0.000126	-0.000106	-0.000326**	-6.58e-05	-0.000215	7.68e-05
	(9.33e-05)	(0.000142)	(0.000102)	(4.19e-05)	(0.000236)	(3.56e-05)
Cloud Coverage (oktas)	0.000242*	0.000373	0.000219	0.000358	-0.000137	0.000234**
	(0.000123)	(0.000318)	(0.000372)	(0.000251)	(0.000472)	(4.39e-05)
Rain Indicator	0.000209	0.000726	-0.00103	-2.18e-05	-3.64e-05	0.000781**
	(0.000595)	(0.00113)	(0.00105)	(0.000158)	(0.000769)	(0.000192)
Snow Indicator	-0.00260	0.00632**	-0.000403	0.00228	0.00437	-0.00110
	(0.00180)	(0.000802)	(0.00267)	(0.00160)	(0.00775)	(0.000535)
Fog Indicator	-8.11e-05	0.00177	-1.76e-05	0.00186	-0.00277**	0.000834***
	(0.000533)	(0.00190)	(0.000541)	(0.00208)	(0.000794)	(0.000110)
Dew Point (Fahrenheit)	-9.78e-05	-8.17e-06	0.000207	-2.14e-05	0.000218	-0.000175***
	(6.54e-05)	(0.000114)	(0.000113)	(5.32e-05)	(0.000196)	(2.56e-05)
Visibility (miles)	-1.21e-05	0.000443	0.000258	0.000780*	-0.000387	0.000218
	(0.000221)	(0.000194)	(0.000373)	(0.000310)	(0.000435)	(9.77e-05)
Wind Speed (knots)	0.000127*	-0.000157	-6.58e-05	0.000141	0.000217	-0.000150**
	(6.58e-05)	(0.000371)	(0.000142)	(0.000163)	(0.000200)	(2.92e-05)
County FE X Year FE	X	X	X	X	X	X
Day of the Week FE	X	X	X	X	X	X
Week of the Year FE X Region FE	X	X	X	X	X	X
Patient FE	X	X	X	X	X	X
Observations	534,496	111,113	482,128	400,117	311,261	615,351
R-squared	0.001	0.001	0.001	0.001	0.001	0.001
Number of Patients	94,745	24,064	96,576	88,639	74,153	93,292

Notes: Medical data at the patient-day level. Weather data at the county-day level. Period is 01/01/2003-12/31/2004. The dependent variable is an indicator for filling antidepressant prescription on the day of the appointment. Only includes outpatient appointments with a medical professional who is able to prescribe drugs. Only includes appointments in which the major diagnosis is that of a mental disease or disorder. Enrollee characteristics include age, gender, employee classification, employment status, and relation to the employee. Standard errors clustered at the climatic region level. Climatic regions follow the classification of the National Centers for Environmental Information (Karl and Koss, 1984) as per Figure 2.6.

Table 2.8: Antidepressant Filling on Appointment Day, by Season

	Spring	Summer	Fall	Winter
Fills Antidepressant Indicator	(1)	(2)	(3)	(4)
Temperature (Fahrenheit)	-0.000178	-0.000161	-0.000187*	3.21e-05
	(0.000118)	(0.000166)	(8.66e-05)	(7.57e-05)
Cloud Coverage (oktas)	3.60e-06	0.000141	-0.000128	0.000838***
	(0.000243)	(0.000210)	(0.000117)	(0.000145)
Rain Indicator	0.000475	-0.000861	0.000332	0.00163
	(0.000992)	(0.00138)	(0.000837)	(0.00173)
Snow Indicator	-0.00352*	-0.00188	0.000551	-0.00197
	(0.00162)	(0.0145)	(0.00204)	(0.00162)
Fog Indicator	0.00260**	0.00110	-0.00217	7.05e-05
	(0.00111)	(0.00114)	(0.00119)	(0.00190)
Dew Point (Fahrenheit)	4.40e-06	9.64e-05	0.000177	-0.000177**
	(0.000108)	(0.000123)	(9.94e-05)	(7.14e-05)
Visibility (miles)	0.000133	3.48e-05	0.000262	0.000421
	(8.51e-05)	(0.000345)	(0.000226)	(0.000236)
Wind Speed (knots)	5.98e-05	8.69e-05	0.000170	-8.84e-05
	(9.28e-05)	(0.000291)	(0.000123)	(0.000152)
County FE X Year FE	X	X	X	X
Day of the Week FE	X	X	X	X
Week FE X Region FE	X	X	X	X
Patient FE	X	X	X	X
Observations	654,376	617,866	627,874	600,775
R-squared	0.001	0.001	0.001	0.001
Number of Patients	222,688	220,106	224,394	231,712

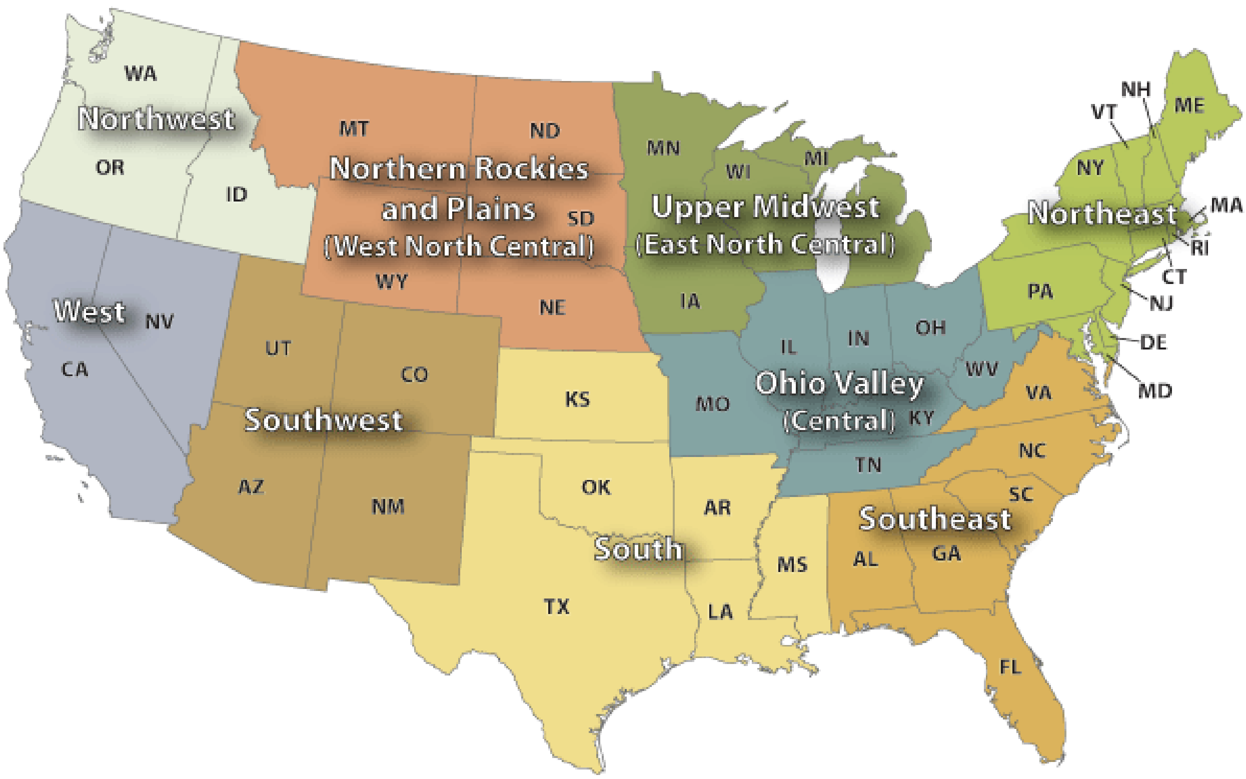
Notes: Medical data at the patient-day level. Weather data at the county-day level. Period is 01/01/2003-12/31/2004. The dependent variable is an indicator for filling antidepressant prescription on the day of the appointment. Only includes outpatient appointments with a medical professional who is able to prescribe drugs. Only includes appointments in which the major diagnosis is that of a mental disease or disorder. Enrollee characteristics include age, gender, employee classification, employment status, and relation to the employee. Standard errors clustered at the climatic region level. Climatic regions follow the classification of the National Centers for Environmental Information (Karl and Koss, 1984) as per Figure 2.6.

Table 2.9: Antidepressant Filling on Appointment Day, by Dosing

	Minimum Dose		Intermediate		Maximum Dose	
Fills Antidepressant Indicator	(1)	(2)	(3)	(4)	(5)	(6)
Temperature (Fahrenheit)	-2.33e-05	-3.85e-05	-1.09e-05	-4.71e-05	5.19e-06	9.56e-06
	(3.18e-05)	(4.41e-05)	(4.86e-05)	(3.39e-05)	(1.41e-05)	(1.46e-05)
Cloud Coverage (oktas)	-1.04e-05	-4.75e-06	0.000130**	0.000124*	6.21e-05	5.64e-05*
	(6.24e-05)	(5.30e-05)	(5.23e-05)	(6.20e-05)	(3.53e-05)	(2.95e-05)
Rain Indicator	2.46e-05	-6.30e-05	-3.77e-05	0.000193	2.78e-05	6.04e-05
	(0.000294)	(0.000317)	(0.000115)	(0.000346)	(0.000154)	(0.000207)
Snow Indicator	0.000129	-2.14e-05	-0.000399	-0.000941***	-0.000347	-0.000448
	(0.000220)	(0.000296)	(0.000520)	(0.000233)	(0.000347)	(0.000423)
Fog Indicator	0.000157	-0.000179	0.000210	-2.18e-05	0.000183	0.000434**
	(0.000364)	(0.000293)	(0.000131)	(0.000274)	(0.000127)	(0.000157)
Dew Point (Fahrenheit)	4.15e-05*	2.74e-05	-3.50e-05	-1.38e-05	-1.35e-05	-1.99e-05
	(2.16e-05)	(4.03e-05)	(3.53e-05)	(2.16e-05)	(1.66e-05)	(1.90e-05)
Visibility (miles)	1.96e-05	9.10e-06	3.02e-05	5.27e-05	4.77e-05	5.50e-05
	(8.02e-05)	(5.69e-05)	(8.00e-05)	(0.000105)	(5.52e-05)	(7.59e-05)
Wind Speed (knots)	1.16e-05	2.48e-05	-5.77e-05	-3.62e-06	2.59e-06	2.04e-05
	(1.61e-05)	(3.51e-05)	(7.86e-05)	(6.62e-05)	(1.80e-05)	(1.80e-05)
County FE X Year FE	X	X	X	X	X	X
Day of the Week FE	X	X	X	X	X	X
Week FE X Region FE	X	X	X	X	X	X
Patient Characteristics	X		X		X	
Patient FE		X		X		X
Mean of dependent variable	0.0189	0.0189	0.0342	0.0342	0.0130	0.0130
Observations	2,500,891	2,500,891	2,500,891	2,500,891	2,500,891	2,500,891
R-squared	0.002	0.000	0.001	0.004	0.000	0.002
Number of Patients	483,333	483,333	483,333	483,333	483,333	483,333

Notes: Medical data at the patient-day level. Weather data at the county-day level. Period is 01/01/2003-12/31/2004. Minimum/Maximum Dose only includes drugs with the minimum/maximum dosing within a drug product. The dependent variable is an indicator for filling antidepressant prescription on the day of the appointment. Only includes outpatient appointments with a medical professional who is able to prescribe drugs. Only includes appointments in which the major diagnosis is that of a mental disease or disorder. Enrollee characteristics include age, gender, employee classification, employment status, and relation to the employee. Standard errors clustered at the climatic region level. Climatic regions follow the classification of the National Centers for Environmental Information (Karl and Koss, 1984) as per Figure 2.6.

Figure 2.6: Climatic Regions of the Contiguous United States



Source: National Centers for Environmental Information (Karl and Koss, 1984)

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Appendix A

Appendix

A.1 The 5-star Rating System

Private Medicare Part D insurers are evaluated on 17 measures, which are designed to capture the quality of the service provided, regardless of prices and costs. The Centers for Medicare and Medicaid Services uses information from various sources to evaluate plans, including (i) data on plan enrollment and beneficiary prescription drug usage; (ii) the Consumer Assessment of Healthcare Providers and Systems, an annual survey conducted by the U.S. Agency for Healthcare Research and Quality; (iii) data from insurers' call centers; (iv) drug pricing accuracy data; (iv) consumer complaints, appeals, and independent reviews of disputes.[1] The seventeen measures are:

1. How long pharmacists wait on hold when they call the plan's pharmacy help desk.
2. The availability of TTY/TDD services and foreign language interpretation at the insurer's call center.
3. How often the drug plan does not meet Medicare's deadlines for timely appeals decisions.
4. How often an independent reviewer agrees with the drug plan's decision to deny a member's appeal.
5. The percentage of enrollment requests that the plan sends to CMS within 7 days.
6. The number of complaints CMS receives about the drug plan.
7. The number of problems CMS finds in members' access to services and in the plan's performance (audits).
8. The percentage of plan members who chose to leave the plan.
9. "How easy it is to get information about prescription drug coverage and cost from the drug plan ," as per members' evaluation.
10. Members' overall rating of plan.

[1] A detailed description of measures, data sources, and on how the different measures are aggregated into the star rating is found in Centers for Medicare and Medicaid Services (2012).

11. "How easy it is to get the prescription drugs needed," as per members' evaluation.
12. Whether the plan provides accurate price information and keeps drug prices stable during a year.
13. The percentage of plan members who get prescriptions for certain drugs with a high risk of serious side effects, when there may be safer drug choices.
14. The percentage of the members with both diabetes and high blood pressure who are prescribed a recommended medication.
15. The percentage of members with a prescription for a diabetes medication who fill their prescription often enough.
16. The percentage of members with a prescription for a blood pressure medication who fill their prescription often enough.
17. The percentage of members with a prescription for a cholesterol medication who fill their prescription often enough.

A.2 Simplest Versions of the Models

Option Value

This section studies the behavior of a fully-rational un-enrolled beneficiary in a simple model with two health conditions (healthy and sick) and three plans (5-star, non-5 star, outside option). I use the model to derive predictions of the impact the policy change has on enrollment and adverse selection. As the average 5-star plan has a larger premium and a lower deductible and co-pays than other plans, I assume the 5-star plan yields a higher instantaneous payoff than the non-5 star plan for the sick, and *vice versa*. I assume that sick is an absorbing state, and that the healthy face a positive probability of becoming sick. Pre-policy change, enrollment in any plan can only happen by the deadline. Post-policy change, beneficiaries can enroll in the 5-star plan at any time. The length of a time period is a month and a beneficiary lives indefinitely.

More specifically, an un-enrolled beneficiary with health state $h \in \{n, s\}$ chooses a drug coverage plan $p \in \{p^o, p^1, p^5\}$. At the original deadline, $t = 0$, a healthy beneficiary, n, estimates she will become sick, s, with probability $p > 0$. I assume that s is an absorbing state. Uncertainty resolves at $t = 1$, and health states do not change thereafter. Switching plans costs $c > 0$.

The monthly instantaneous net benefit each plan yields for each health state, with respect to the outside option p^o, is given by:

$$u(n, p^5) - u(n, p^o) = b^{5n},\ u(s, p^5) - u(s, p^o) = b^{5s},$$

$$u(n, p^1) - u(n, p^o) = b^{1n}, \text{ and } u(n, p^1) - u(n, p^o) = b^{1s}.$$

To keep the model as simple as possible, I assume $b^{5s} > b^{1s} = 0$ and $b^{1n} > b^{5n} = 0$.

I compare the behavior of an individual post-policy change to what the same beneficiary would have done were the deadline for enrollment in 5-star plans still in vogue. The policy might lead to changes in behavior of the healthy if they expect to switch to p^5 after the deadline when they become sick: $c < \frac{\delta}{1-\delta}(b^{5s})$. In that case, the policy change leads to an increase in the expected payoff, via option value, that the healthy derives from both p^o and p^1. Hence, she will be less prone to enroll in p^5 by the original deadline, and might switch to p^5 upon becoming sick. Both responses lead to an increase in adverse selection in p^5.

Table A.1 presents all possible combinations of pre- and post-policy change behaviors as a function of the primitives of the model.

On case A.3, both health risk and switching cost are high. The possibility of waiting to switch to the 5-star plan when she becomes sick makes a healthy beneficiary remain un-enrolled. The same beneficiary would have enrolled in the 5-star plan had the policy not been implemented.

On case A.4, health risk is high and switching cost is low. The possibility of switching to the 5-star plan when she becomes sick makes a healthy beneficiary enroll in the non-5 star plan by the original deadline. She takes advantage of the higher payoff that plan offers in comparison to the outside option for the healthy. The same beneficiary would have enrolled in the 5-star plan had the policy not been implemented.

Other cases include A.6, which shares the intuition of case A.3. Additionally, on case A.7 a beneficiary who would not have enrolled in any plan now enrolls in the non-5 star plan. That case has a small measure on set of possible parameters. In fact, it depends on δ being sufficiently now, which might be implausible.

On cases A.2-A.10, the beneficiary switches to p^5 when she becomes sick. In all these cases, the beneficiary is better off after the policy change.

On cases A.1, B-1-B.4, the policy change does not impact the behavior of the beneficiary.

Predictions are summarized on Figure 1.3c.

Present Bias

This section discusses a model in which an un-enrolled present-biased beneficiary chooses among three plans (5-star, non-5 star, and the outside option). She faces no uncertainty with regards to future health, and switching plans is costly. I assume that the degree of a beneficiary's present bias is not related to other fundamentals such as health status. This is a restrictive assumption. I use the model to derive predictions of the impact of the policy change on enrollment in 5-star and non-5-star plans, and on general take-up. Pre-policy change, enrollment in all plans is only possible by the deadline. Post-policy change, beneficiaries can enroll in 5-star plans at any time. Following section 1.3, I assume that the only opportunity to enroll in a non-5 star plan takes place by the original deadline. The length of a time period is a month and a beneficiary lives indefinitely.

I incorporate present bias via the assumption of hyperbolic discounting, as in Laibson (1997) and O'Donoghue and Rabin (1999). Hyperbolic discounting assumes that the intertemporal utility function a beneficiary holds at each period t is given by

$$U^t(u_t, u_{t+1}, ..., u_T) = u_t + \beta \sum_{\tau=t+1}^{T} \delta^\tau u_\tau,$$

where u_t is instantaneous utility, δ is long-run time-consistent impatience, and $\beta \in [0, 1]$ is a parameter that captures present-bias. The model nests exponential discounting as the special case $\beta = 1$. I restrict attention to naï¿œve beneficiaries, who at each point in time are fully unaware of their future present bias. Naï¿œfs plan future behavior as if they were exponential discounters. In what follows, I compare the post-policy change behavior of an individual to what that same beneficiary would have done were the deadline for enrollment in 5-star plans still in vogue. I focus on a specific beneficiary, and hence omit an individual subscript. Without loss of generality, I restrict attention to three plans: the preferred 5-star plan, the preferred non-5-star plan, and the outside option. In a model with perfect-information and no health risk, all other plans are dominated and would not be chosen.

More specifically, an un-enrolled beneficiary with constant health state h chooses a drug coverage plan $p \in \{p^o, p^1, p^5\}$. Switching plans costs $c > 0$. The monthly instantaneous net benefit each plan yields for a beneficiary with constant health h, with respect to the outside option p^o, is given by:

$$u(h, p^5) - u(h, p^o) = b^5 \text{ and } u(h, p^1) - u(h, p^o) = b^1.$$

Table A.2 presents all possible combinations of pre- and post-policy change behaviors as a function of the primitives of the model. In two cases, the removal of deadlines for enrollment in the 5-star plan leads to procrastination.

On case A.2, the un-enrolled beneficiary would have enrolled in the 5-star plan by the original deadline, as $c < \frac{\beta\delta}{1-\delta}b^5$. As $c < \frac{\delta}{1-\delta}b^5$, the beneficiary thinks she will enroll in the 5-star plan next month if she does not do so by the deadline, but fails to enroll when next month comes because $\frac{\beta\delta}{1-\beta\delta}b^5 < c$. This effect is illustrated on Figure A.1.

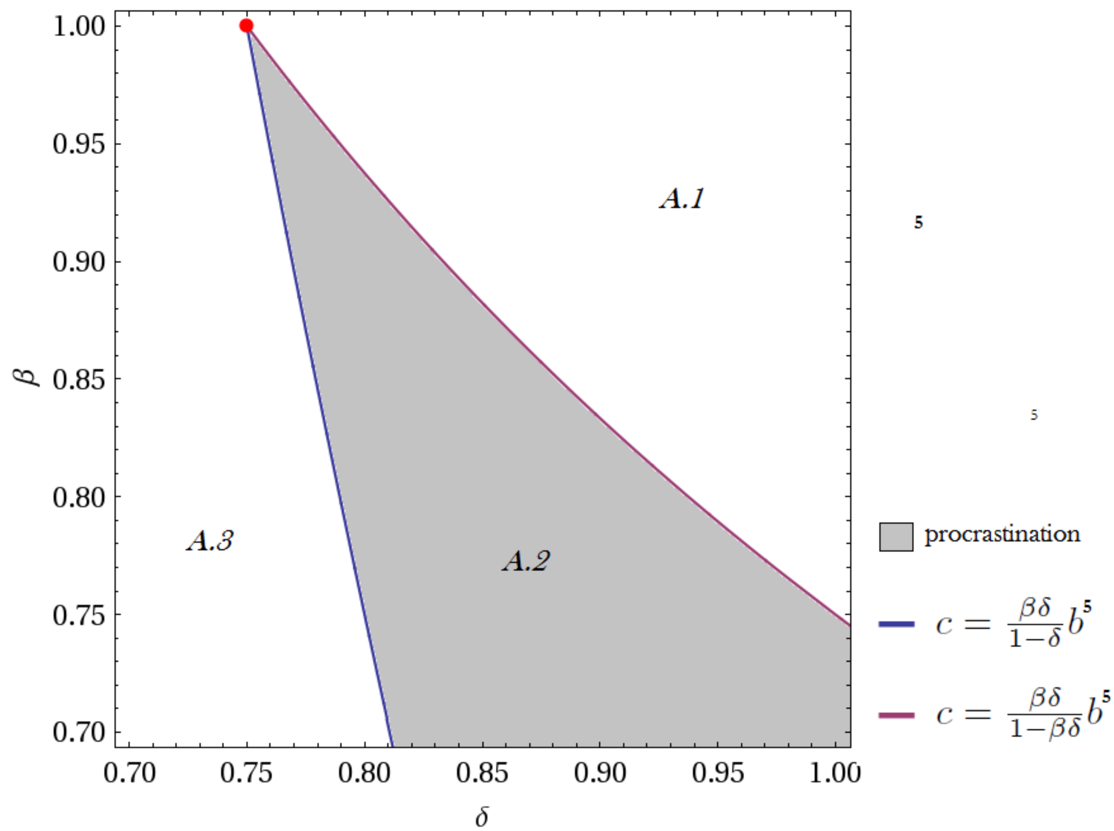
On case B.2, the un-enrolled beneficiary would have enrolled in the non-5 star plan by the original deadline, as $c < \frac{\beta\delta}{1-\delta}b^1$. As $c < \frac{\delta}{1-\delta}b^5$, the beneficiary thinks she will enroll in the 5-star plan next month if she does not enroll in the non-5 star plan by the deadline. In fact, she prefers to enroll in the otherwise sub-optimal 5-star plan tomorrow, as $c > \frac{\beta\delta}{(1-\beta\delta)(1-\delta)}\left(b^1 - \delta b^5\right)$. When next month arrives, however, she fails to enroll in the 5-star plan because $c > \frac{\beta\delta}{(1-\beta\delta)(1-\delta)}\left(b^1 - \delta b^5\right)$ implies $c > \frac{\beta\delta}{(1-\beta\delta)(1-\delta)}\left(b^5 - \delta b^5\right)$ if $b^5 < b^1$. This effect is illustrated on Figure A.2.

Predictions are summarized on Figure 1.3d. In all cases, when a beneficiary's behavior is changed by the removal of deadlines, the consumer is made worse-off under the welfare analysis typically applied in the present bias literature (O'Donoghue and Rabin [1999]).

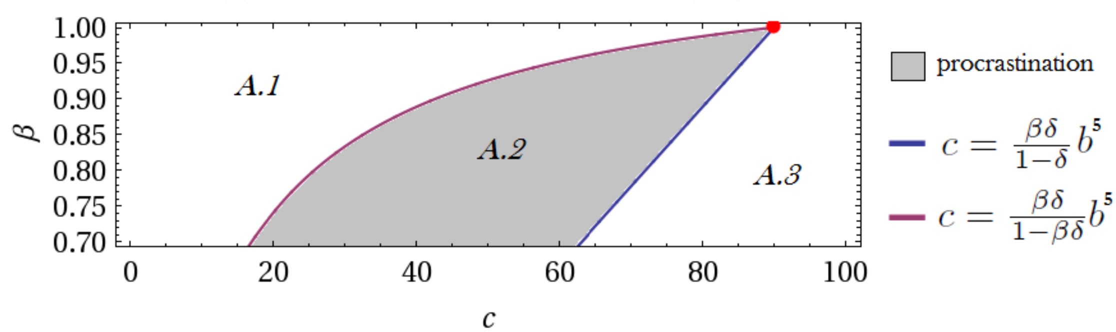
Figure A.1: Present Bias Model, Procrastination in Case A

Beneficiary Prefers 5-star to Non-5-star Plan

(a) Change in behavior as a function of (β, δ), with $c = 30$.



(b) Change in behavior as a function of (β, c), with $\delta = 0.95$.

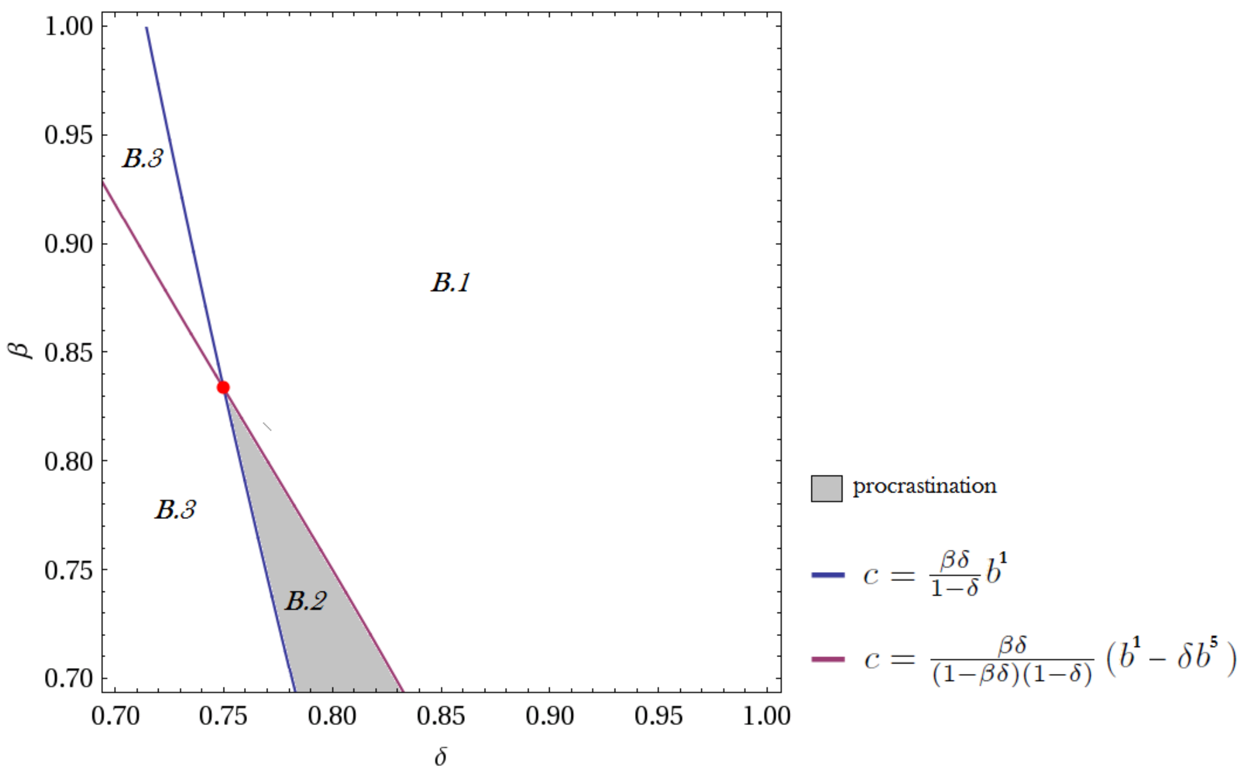


Parameters used: $b^{\star} = 10$ and $b < b^{\star}$. Figure A.2a uses c=30. Figure A.2b uses $\delta = 0.95$.
Notes: All possible combinations of pre- and post-policy change behavior in the model of Section A.2. Cases A.1, A.2, and A.3 are explained on Table A.2

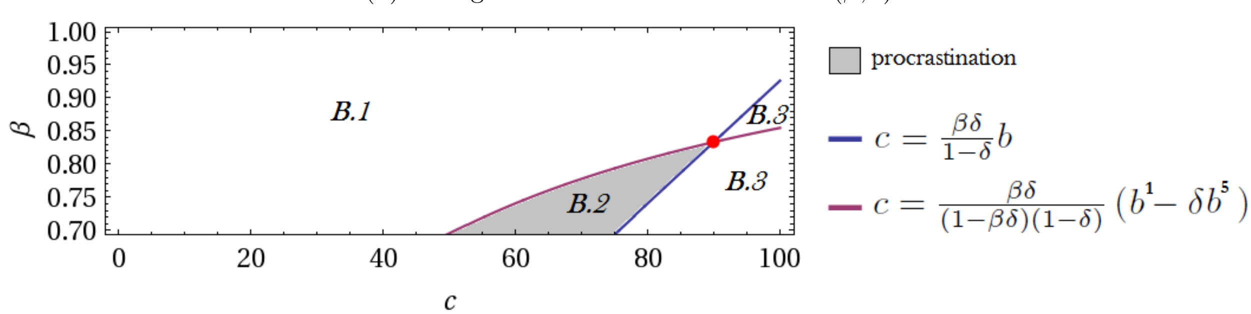
Figure A.2: Present Bias Model, Procrastination in Case B

Beneficiary Prefers Non-5-star to 5-star Plan

(a) Change in behavior as a function of (β, δ)



(b) Change in behavior as a function of (β, c)



Parameters used: $b = 12$ and $b^{\star} = 10$. Figure A.3a uses c=30. Figure A.3b uses $\delta = 0.95$.
Notes: All possible combinations of pre- and post-policy change behavior in the model of Section A.2. Cases B.1, B.2, and B.3 are explained on Table A.2

Table A.1: Simplest Option Value Model - Effect of the Policy on Enrollment and Welfare

Case		Enrollment Orig. Deadline		Consumer Welfare
		Pre Policy	*Post Policy*	*Post - Pre*
A - After Deadline, switches to 5-star if become sick: $c < \frac{\delta}{1-\delta}b^{5s}$				
High health risk, high switching cost: $pb^{5s} > (1-p)b^{1n}$, $c > \left(\frac{1-p}{p}\right)\left(\frac{1+\delta}{1-\delta}\right)b^{1n} - b^{5s}$				
A.1	$c < \frac{\delta}{1-\delta p}pb^{5s}$	5-star	5-star	$= 0$
A.2	$\frac{\delta}{1-\delta p}pb^{5s} < c < \frac{\delta}{1-\delta}pb^{5s}$	**5-star**	**un-enrolled**	$\mathbf{> 0}$
A.3	$c > \frac{\delta}{1-\delta}pb^{5s}$	un-enrolled	un-enrolled	> 0
High health risk, low switching cost: $pb^{5s} > (1-p)b^{1n}$, $c < \left(\frac{1-p}{p}\right)\left(\frac{1+\delta}{1-\delta}\right)b^{1n} - b^{5s}$				
A.4	$c < \min\left\{\frac{\delta}{1-\delta p}pb^{5s} \frac{\delta}{1-\delta p}\frac{(1-p)}{(1-\delta)}b^{1n}\right\}$	**5-star**	**non-5-star**	$\mathbf{> 0}$
A.5	$c > \max\left\{\frac{\delta}{1-\delta p}pb^{5s}, \frac{\delta}{1-\delta p}\frac{(1-p)}{(1-\delta)}b^{1n}\right\}$	un-enrolled	un-enrolled	> 0
A.6	$\frac{\delta}{1-\delta p}pb^{5s} > c > \frac{\delta}{1-\delta p}\frac{(1-p)}{(1-\delta)}b^{1n}$	**5-star**	**un-enrolled**	$\mathbf{> 0}$
A.7*	$\frac{\delta}{1-\delta p}\frac{(1-p)}{(1-\delta)}b^{1n} > c > \frac{\delta}{1-\delta p}pb^{5s}$	**un-enrolled**	**non-5-star**	$\mathbf{> 0}$
Low health risk: $pb^{5s} < (1-p)b^{1n}$				
A.8	$c < \frac{\delta}{1-\delta p}\frac{(1-p)}{(1-\delta)}b^{1n}$	non-5-star	non-5-star	> 0
A.9	$\frac{\delta}{1-\delta p}\frac{(1-p)}{(1-\delta)}b^{1n} < c < \frac{\delta}{1-\delta}(1-p)b^{1n}$	**non-5-star**	**un-enrolled**	$\mathbf{> 0}$
A.10	$c > \frac{\delta}{1-\delta}(1-p)b^{1n}$	un-enrolled	un-enrolled	> 0
B - After Deadline, does not switch to 5-star if become sick: $\frac{\delta}{1-\delta}b^{5s} < c$				
High health risk: $pb^{5s} > (1-p)b^{1n}$				
B.1	$c < \frac{\delta}{1-\delta}pb^{5s}$	5-star	5-star	$= 0$
B.2	$c > \frac{\delta}{1-\delta}pb^{5s}$	un-enrolled	un-enrolled	$= 0$
Low health risk: $pb^{5s} < (1-p)b^{1n}$				
B.3	$c < \frac{\delta}{1-\delta}(1-p)b^{1n}$	non-5-star	non-5-star	$= 0$
B.4	$c > \frac{\delta}{1-\delta}(1-p)b^{1n}$	un-enrolled	un-enrolled	$= 0$

Notes: All possible combinations of pre- and post-policy change behavior of the healthy in the model of Section A.2. The sick do not change behavior in that model. Summary of predictions are found in Figure 1.3c. In all cases in A, the healthy beneficiary switches to the 5-star plan after the original deadline when she becomes sick. (*) Case A.7. requires $\frac{(1-p)}{(1-\delta)}b^{1n} > \frac{1-\delta p}{\delta}c > pb^{5s}$ and $pb^{5s} > (1-p)b^{1n}$, which requires a low δ.

Table A.2: Simplest Present Bias Model - Effect of the Policy on Enrollment and Welfare

Case	*Parameter*	Enrollment		Consumer Welfare
		Pre Policy	*Post Policy*	*Post - Pre*
		A - Prefers 5-star to non-5-star plan: $b^5 > b^1$		
A.1	$c < \frac{\beta\delta}{1-\beta\delta}b^5$	5-star	5-star	$= 0$
A.2	$\frac{\beta\delta}{1-\beta\delta}b^5 < c < \frac{\beta\delta}{1-\delta}b^5$	**5-star**	**un-enrolled**	$\boldsymbol{< 0}$
A.3	$c > \frac{\beta\delta}{1-\delta}b^5$	un-enrolled	un-enrolled	$= 0$
		B - Prefers non-5-star to 5-star plan: $b^5 < b^1$		
		Low switching cost: $c < \frac{\delta}{1-\delta}b^5$		
B.1	$c < \frac{\beta\delta}{(1-\beta\delta)(1-\delta)}\left(b^1 - \delta b^5\right)$	non-5-star	non-5-star	$= 0$
B.2	$\frac{\beta\delta}{(1-\beta\delta)(1-\delta)}\left(b^1 - \delta b^5\right) < c < \frac{\beta\delta}{1-\delta}b^1$	**non-5-star**	**un-enrolled**	$\boldsymbol{< 0}$
B.3	$c > \frac{\beta\delta}{1-\delta}b^1$	un-enrolled	un-enrolled	$= 0$
		High switching cost: $c > \frac{\delta}{1-\delta}b^5$		
B.3	$c < \frac{\beta\delta}{1-\delta}b^1$	non-5-star	non-5-star	$= 0$
B.4	$c > \frac{\beta\delta}{1-\delta}b^1$	un-enrolled	un-enrolled	$= 0$

Notes: All possible combinations of pre- and post-policy change behavior of the healthy in the model of Section A.2. Table does behavior, not plans for future behavior. Cases A.1, A.2, are A.3 are illustrated on Figure A.1. Cases B.1, B.2, and B.3 are illustrated on Figure A.2. Summary of predictions are found in Figure 1.3d.

Table A.3: Monthly County-Level Take-Up of Medicare Part D, Adding 2013 Data

	Jan 2009-Dec 2012		Jan 2009-Dec 2013	
$ln\,(TakeUp_{ct}/\,(1-TakeUp_{ct}))$	Microdata	Aggregate data	Aggregate data	
	(1)	(2)	(3)	(3)
FiveStar^{cnty}	-0.000403	0.00241	-0.00153	0.00732
	(0.0119)	(0.0137)	(0.0156)	(0.0160)
FiveStar^{cnty} × Post	**-0.0532***	**-0.0528***	**-0.0893***	**-0.0884****
	(0.0289)	**(0.0298)**	**(0.0491)**	**(0.0440)**
Controls				
× Region FE	x	x	x	
× Region-Year FE				x
Region-Year FE	x	x	x	x
Average Effect	-0.0283*	-0.0275*	-0.0458*	-0.0453**
	(0.0154)	(0.0155)	(0.0252)	(0.0226)
Sample	All	All	All	All
Observations	152,904	153,201	191,325	191,325
Averate Take-Up	0.4681	0.4794	0.4874	0.4874
R-squared	0.278	0.223	0.387	0.485
Number of SSA Counties	3,186	3,192	3,189	3,189

Notes: Each observation is measured at the county-month level.FiveStar^{cnty} is an indicator variable for a county within the coverage area of a 5-star Part D insurer. The variable of interest is FiveStar^{cnty}PostPeriod, where PostPeriod is an indicator for the post-policy change period. The control variables included are mean premium and deductible of Part D plans, as well as mean star-classification, average number of plans offered by, and total number of Part D insurers. All specifications include county and time fixed effects. County divisions follow the Social Security Administration classification. Standard errors are clustered at the state level.