Adverse Selection and Technological Change: Evidence from Medicare Part D*

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Abstract

New medical technologies are increasingly expensive. These high-cost innovations make generous health insurance coverage more valuable for individuals at risk of needing new therapies. However, if those individuals are also costlier to insure, innovation may generate adverse selection. I develop a conceptual framework to study this trade-off and examine it empirically using data from Medicare Part D, the prescription drug insurance program for the elderly. I first show that an innovation shock driven by high-cost new drug approvals in the mid-2010s generated substantial adverse selection against Part D plans with generous coverage for those drugs, increasing those plans' average costs by 35%. In the years following the shock, the market exhibits hallmark patterns of dynamic adverse selection: switchers into generous coverage are high-cost and more likely to use the new drugs; premiums rise by 52%; and price sensitive low-cost enrollees switch out of generous plans. Ultimately, the market significantly unravels, as the market share for the generous plans falls by 49%. Using a structural model of plan choice, I show that this unraveling leads to inefficiently low equilibrium enrollment in the generous plans and raises prices for those who remain enrolled, substantially reducing the insurance value of generous coverage and decreasing *ex-ante* social surplus. More robust reinsurance and risk adjustment policies would limit the losses from selection.

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1 Introduction

In recent decades, expensive new medical technologies have proliferated rapidly, from gene therapies for rare conditions to widely-sought breakthrough drugs such as Sovaldi and Ozempic. While the clinical promise of these innovations has led some to term this a "golden age for medicine" (Wallace-Wells, 2023), breakthroughs in medical technology have also been accompanied by concerns about affordability and high costs for consumers (Kolata and Paris, 2023).

Health insurance exists to help defray these costs. Indeed, because high-cost new medical innovation raises the variance of medical spending, it makes generous insurance more valuable for individuals at risk of needing a new therapy. However, if those individuals are more costly to insure, then technological change may also generate adverse selection. This link between value and cost is a foundational element of selection in insurance markets, and an extensive literature has documented its consequences, including distorted contract offerings and market unraveling (Akerlof, 1970; Rothschild and Stiglitz, 1976; Cutler and Reber, 1998).[1]

High-cost technological change therefore raises a potential trade-off in health insurance markets: while it makes generous coverage more valuable, it may simultaneously make that coverage harder for the market to sustain. The extent to which this occurs is an empirical question with important implications for the value of insurance and the availability of generous coverage in equilibrium. These implications matter not only for economic theory but also for ongoing policy debates about how best to shore up insurance markets as demand grows for new high-cost medications (Robbins, 2024).

In this paper, I evaluate the trade-off between value and selection conceptually and empirically. I start by outlining a conceptual framework detailing the interaction between innovation, selection, and insurance equilibria. I then estimate the causal effect of technological change on health insurance markets and provide evidence that it generates adverse selection. Finally, I use a structural model to estimate demand and cost curves directly, evaluate changes in selection, and quantify the losses associated with selection under the observed equilibrium and counterfactual policies.

I start by developing a conceptual framework that formalizes how new medical innovation

[1]For a more complete review of this literature, please see Geruso and Layton (2017) and Einav and Finkelstein (2023).

and adverse selection interact. The approach starts from the workhorse Cutler and Zeckhauser (2000) model of health insurance and extends it to incorporate technological change. In the model, consumers choose between purchasing insurance I or going uninsured U, and I evaluate how these choices evolve (and how they co-vary with costs) as technology changes. I derive a simple formula decomposing the effect of technological change on selection into three pieces: (1) pre-innovation sorting; (2) differential demand responses to innovation (adverse selection); and (3) the extent to which changes in demand are correlated with changes in cost. Taken together, these terms capture the extent to which technological change influences how strongly insurance demand selects on individual costs. Each term also has an intuitive graphical interpretation, which I illustrate using the standard Einav et al. (2010) (EFC) graph-theoretic framework.

Next, I estimate the causal effect of technological change on insurance markets. I study standalone prescription drug plans in Medicare Part D, the prescription drug insurance program for the elderly in the United States, where more than 22 million Americans choose from a set of plans each year (Cubanski and Damico, 2024). Using administrative Part D data, I first empirically document a large innovation shock that hit the Part D market in the mid-2010s. The shock was driven by the 2013 and 2014 cohorts of FDA-approved drugs that included a variety of expensive and widely-used therapies such as Hepatitis C cures, Type 2 diabetes medications, and new cancer therapies (Mullard, 2014, 2015). In the years leading up to the approvals, the average fraction of plan spending on drugs approved in the prior year hovers around 2%, before more than quadrupling with the arrival of these two cohorts of drugs and then returning to pre-2014 levels (Figure 2).

I use this innovation shock as a natural experiment to estimate the effect of high-cost technological change on the Part D market, combining this time series variation in the costliness of new drugs with cross-sectional variation in plans' exposure to the shock to estimate causal effects. To do so, I use cost-sharing rules specific to plans' formulary tiers to identify a set of Part D plans ("high coverage plans") that provided additional coverage in the Part D 'donut hole' for the 2013-2014 drugs and a set of plans that did not offer such coverage ("low coverage plans"). I compare these high coverage and low coverage plans over time in a standard two-way fixed effects framework.[2] I estimate that the innovation shock increases average annual insurer costs for the high

[2]The approach is similar in spirit to the work of Kreider et al. (2024) studying adverse selection on specialty hospital

coverage plans relative to the low coverage plans by $588 per enrollee from 2013-2018, an increase of approximately 35%. Risk adjustment does little to combat these changes, with the innovation shock increasing risk-adjusted costs by $563. These cost increases coincide with small increases in plan risk, as the innovation shock increases the average Part D risk score in the high coverage plans by .026 points (approximately 2.7%). Rising costs and risk bring greater support from federal insurance backstops as well: the innovation shock increases federal reinsurance payments to the high coverage plans by $192 per enrollee per year. Despite these offsets, the rise in payments is less than half of the increase in plan costs.

A natural question is whether these cost changes reflect differences in sorting (adverse selection), greater spending on new drugs induced by generous coverage (moral hazard), or mechanical increases that would arise if individuals with greater use of the new, high-cost innovations were already enrolled in the high coverage plans prior to the new drug approvals. Nearly all of the change in plan costs is driven by spending on drugs *other than* the newly approved drugs, suggesting limited scope for moral hazard. By contrast, these cost increases coincide with changes in the underlying composition of enrollees in the high coverage plans. In the years following the shock, individuals who switch into the high coverage plans are significantly more likely to use the new drugs than incumbent enrollees in the high coverage plans (stayers). The key selection issue is that these switchers in are costlier on *many dimensions*, not only on their use of new drugs, and plan costs rise as a result. All of these demand-side results are consistent with a pattern of dynamic adverse selection.

I then show how these changes affect market equilibrium. As costs rise, plan premiums follow suit: the shock increases premiums by $252 per year (approximately 52%). As prices rise, individuals who switch out of the high coverage plans are disproportionately *low*-cost, exacerbating selection challenges. These patterns are consistent with standard models of an insurance death spiral (Cutler and Reber, 1998). Ultimately, the market for the high coverage plans partially unravels, as the innovation shock reduces the market share for this form of generous coverage by approximately 49% from 2013-2018.

Finally, I combine this reduced form evidence with a structural model of demand for high and low coverage plans to measure changes in selection and evaluate welfare impacts. I use the will-

coverage in Medicaid.

ingness to pay (WTP) estimates from the model of plan choice and construct marginal cost curves in the spirit of Einav et al. (2010). I show that selection against the high coverage plans' generous coverage – as measured by the steepness of these curves – rises sharply in the years following the innovation shock, with the cost increases largest among those with the greatest willingness to pay for generous coverage. Using the structural estimates, I show that approximately 22% of the increase in selection is accounted for by "classical" adverse selection: individuals with larger increases in demand for the high coverage plans are disproportionately expensive to insure at baseline. The remainder is explained by cost increases among those already enrolled in the high coverage plans (13%) and the extent to which changes in demand for the generous plans covary with changes in individuals' costs (65%). These findings are consistent with the reduced form results and conceptual model, underscoring that those with the highest incremental demand for the high coverage plans after the innovation shock are considerably more expensive to insure.

I use the model to assess the welfare consequences of this unraveling. Prior to the innovation shock, there is modest adverse selection against the high coverage plans; the equilibrium enrollment level achieves 90% of the market surplus that would be attained at the efficient level of coverage. In the years following the innovation shock, however, the fraction of individuals enrolled in high coverage plans falls sharply, and equilibrium prices rise. Inefficiently low enrollment in the high coverage plans generates a sizable welfare loss; the equilibrium market surplus is just 57% of the efficient market surplus.

In addition to the welfare losses that come from inefficiently low enrollment, selection also generates implicit transfers across individuals in the market, because individuals who remain enrolled in high coverage plans pay higher prices than they would if more of the market were enrolled. As noted by Hendren (2021), these transfers can be combined with traditional market surplus to estimate the *ex-ante* welfare effects of selection on insurance value. Taking this ex-ante approach, I find that the post-innovation equilibrium achieves just 19% of the surplus that would be achieved at the ex-ante efficient level of coverage, considerably less than the 57% estimated using traditional measures of welfare. Accounting for the effects of selection not only on equilibrium enrollment but also on the prices paid by individuals who remain enrolled in high coverage plans is critical for capturing the full effect of selection on insurance value.

What policies are available to address this unraveling? I study this question by simulating

changes to two Part D programs designed to stabilize the market: risk adjustment and reinsurance. While unraveling is substantial in this market, Part D's reinsurance limits the losses from selection. Reducing the generosity of reinsurance leads to near total unraveling. I estimate that enrollment in the high coverage plans would fall to 1.6% under a less generous Part D reinsurance policy. A more robust risk-adjustment policy helps to stabilize the market, preserving higher enrollment in the high coverage plans, lower prices, and greater social surplus.

Taken together, my results provide conceptual and empirical evidence that technological change can generate adverse selection in insurance markets and that the consequences of that selection are not trivial. As approvals for drugs such as Ozempic and Wegovy accumulate, the design of public policy to stabilize insurance markets for high-cost drugs will only grow in importance.

Related Literature. This paper contributes to a few distinct literatures. The first is an established body of work in public economics on adverse selection in insurance markets (Akerlof, 1970; Rothschild and Stiglitz, 1976; Einav and Finkelstein, 2011; Geruso and Layton, 2017; Einav and Finkelstein, 2023). Many papers have explored the role of adverse selection in insurance markets with choice, and these papers tend to focus on selection on the *price* of coverage (i.e., plan premiums) (Cutler and Reber, 1998; Einav et al., 2010; Bundorf et al., 2012; Finkelstein et al., 2019). In recent years, there has been more attention paid to how selection may occur on non-price dimensions of plan design, such as hospital networks (Shepard, 2022; Kreider et al., 2024).

Despite the importance of insurance markets for smoothing the costs of expensive new innovations, relatively little research has examined the interaction between insurance markets and technological change. This paper is most closely related to a small literature that has explored how insurers' equilibrium coverage choices for drugs reflect selection incentives, in the spirit of Rothschild and Stiglitz (1976) (Jacobs and Sommers, 2015; Carey, 2017; Lavetti and Simon, 2018; Geruso et al., 2019). Yet, these papers all consider insurance markets in equilibrium, whereas I explore the dynamics of selection in this project. This work is also related to a small literature on the intersection of insurance and innovation that has underscored the implicit insurance value of medical innovation, which reduces health risks in the sick state of the world, and emphasized the role of insurance in mitigating some of the inefficiencies created by the patent system (Lakdawalla et al., 2017; Lakdawalla and Sood, 2009). I extend this work by examining both demand- and

supply-side responses to innovation in insurance markets.

This paper proceeds as follows. In Section 2, I outline a conceptual framework detailing the interaction between adverse selection and technological change. In Section 3, I provide background on my empirical setting and data from Medicare Part D. Section 4 outlines my empirical strategy and identifying variation. In Section 5, I present reduced form evidence of the effect of technological change on the Part D insurance market. Section 6 details my structural model and provides estimates of selection and welfare. Section 7 concludes.

2 Conceptual Framework

I begin with a conceptual framework that illustrates the effects of technological change on markets with selection, beginning from the workhorse Cutler and Zeckhauser (2000) model of insurance value and extending it to include technological change.

2.1 Setup

Individuals (i) get utility u from non-medical consumption x and their health h, which is a function of medical spending m. Utility $u(x, h(m))$ is strictly increasing and concave. For simplicity, I begin with a model where there are two states of the world. In the sick state, which occurs with probability π, individuals incur medical spending m in order to fully restore their health. In the healthy state, which occurs with probability $1 - \pi$, they incur no medical spending.

Individuals have the choice to purchase insurance I at an actuarially fair premium $p_I = \pi m$ or to be uninsured with premium p_U, which is normalized to zero. With income y, individuals' budget constraints are therefore $y = x + p_I$ when insured and $y = x + p_U + m$ when uninsured. Individuals choose medical spending m and non-medical consumption x to maximize utility u subject to the budget constraints above. These yield utilities u_i^{I*} when insured and u_i^{U*} when uninsured. I assume that individuals maximize expected utility, which can be written:[3]

$$E[u_i^{I*}] = u_i^{I*}(y - p_I)$$
$$E[u_i^{U*}] = (1 - \pi)u_i^{U*}(y - p_U) + \pi u_i^{UI*}(y - p_U - m)$$

[3]The h terms drop out of the expected utility expressions because of the assumption that medical spending m restores one to full health.

Following Cutler and Zeckhauser (2000), approximating $E[u_i^{UI*}]$ by a second-order Taylor expansion allows us to write the value of insurance:

$$\frac{E[u_i^{I*}] - E[u_i^{UI*}]}{u'} = \frac{1}{2}\frac{-u''}{u'}m^2\pi(1-\pi) \tag{1}$$

There are three key terms. The left-hand side is the value of insurance – the difference in expected utility from being insured versus uninsured, converted to dollars by dividing by the marginal utility of consumption. The term $\frac{u''}{u'}$ is the coefficient of absolute risk aversion. Finally, $m^2\pi(1-\pi)$ measures of the variance of medical spending.[4] Note that this formulation assumes that insurance prices are actuarially fair (i.e., individual-specific pricing) for simplicity of exposition. In Appendix B.1, I derive a more general formula for the value of insurance that does not rely on individual-specific pricing.

The key objects for measuring changes in selection are individuals' demand and costs. For demand, denote the incremental value of being insured as $V_i = E[u_i^{I*}] - E[u_i^{UI*}]$. Consumers purchase insurance iff $V_i \geq 0 \implies E[u_i^{I*}] \geq E[u_i^{UI*}]$. At a given price p_I, let $s \in [0,1]$ denote the fraction of individuals that purchase insurance, where the individuals with the greatest willingness to pay for insurance are those purchasing insurance when s is small. Let costs for individual i be given by $C_{i,j}$, where $j \in \{U, I\}$ allows for different costs when insured and uninsured to capture moral hazard.

Technological Change. Technological change is characterized by changes in the function that maps medical spending to health. For simplicity, I consider a world where there are two technology regimes. In the baseline period, technology g translates medical spending m to health $h(m_g^*) = g(m_g^*)$. In the post-innovation period, medical technology is k, and health is $h(m_k^*) = k(m_k^*)$. Medical spending varies with the technology regime, allowing for a different optimal levels of spending under different sets of technologies.

For the purposes of the model, I make a few assumptions about the nature of innovation. First, I assume that innovation increases both the mean and variance of medical spending m, i.e., $\overline{m}_k > \overline{m}_g$ and $\text{Var}(m_k) > \text{Var}(m_g)$. For many high-cost innovations, these are natural assumptions.

[4] This follows from the fact that $E[m] = \pi m$. Expanding terms, we have $m^2\pi - m^2\pi^2 = E[m^2] - (\pi m)^2 = E[m^2] - (E[m])^2 = \text{Var}(m)$.

Second, I assume that innovation weakly improves health at a given optimal level of spending, that is $h(m_g^*) \leq h(m_k^*)$. That is, new medical technologies do not make individuals strictly worse off, in terms of their health, relative to the baseline technology.

2.2 Changes in Selection

I begin by considering how selection changes with technological change. To measure selection, I take the approach developed by Einav et al. (2010) and evaluate the marginal cost curve, defined as the average cost of individuals with a given incremental value of insurance, $MC(V) = E[C_i|V_i = V]$. The slope of this curve is instructive about the existence of selection, the direction of selection (if any), and the magnitude. A slope of zero suggests no selection, a negative slope suggests adverse selection, and a positive slope suggests advantageous selection. The slope of the marginal cost curve corresponds to the coefficient β in a regression of individual costs on incremental demand for insurance given by $C_i = \alpha + \beta V_i + \varepsilon_i$. Here, $\beta = \frac{\text{Cov}(C_i, V_i)}{\text{Var}(V_i)}$, where the numerator reflects the extent to which demand for insurance selects on individual costs.[5] A larger covariance implies a steeper marginal cost curve.

I define the change in selection as the innovation-induced change in the covariance $\text{Cov}(C_i, V_i)$ between cost and demand for insurance. Intuitively, this approach captures how new medical innovation changes the extent to which demand for insurance selects on individuals' costs. If new medical innovation increases selection on cost, then the slope of the line of best fit of cost projected onto incremental demand should grow in magnitude, and vice versa. In addition to the appealing graphical intuition of this approach, measuring changes in selection in this way also allows me to derive simple formulas decomposing the component pieces of innovation-induced changes in selection.

To see this, recall that there are two periods, a pre-innovation period with technology g and a post-innovation period with technology k. Let the incremental demand for insurance in the post-innovation period be $V_i^k = V_i^g + \Delta V_i$ and the same for individual costs $C_i^k = C_i^g + \Delta C_i$. The change

[5] Shepard and Wagner (2025) refer to this as an "adverse selection tax."

in the covariance between cost and demand is given by:

$$\begin{aligned}\underbrace{\text{Cov}(C_i^k, V_i^k) - \text{Cov}(C_i^g, V_i^g)}_{\Delta \text{ in screening on cost}} &= \text{Cov}(C_i^g + \Delta C_i, V_i^g + \Delta V_i) - \text{Cov}(C_i^g, V_i^g) \\ &= \underbrace{\text{Cov}(\Delta C_i, V_i^g)}_{(1)} + \underbrace{\text{Cov}(C_i^g, \Delta V_i)}_{(2)} + \underbrace{\text{Cov}(\Delta C_i, \Delta V_i)}_{(3)}\end{aligned} \tag{2}$$

There are three terms that summarize how the covariance between insurance demand and cost changes due to technological change:

- **Term (1) (mechanical changes):** The extent to which pre-innovation insurance demand (V_i^g) screens on the innovation-induced change in costs (ΔC_i). In short, do individuals with higher pre-innovation insurance demand see larger innovation-induced cost changes?
- **Term (2) (adverse selection):** The extent to which the innovation-induced change in incremental demand (ΔV_i) screens on pre-innovation costs. Do individuals with greater innovation-induced changes in demand for insurance have higher pre-innovation costs?
- **Term (3) (screening on spending increases):** The extent to which the innovation-induced change in insurance demand (ΔV_i) screens on the innovation-induced change in cost (ΔC_i). Do the individuals with greater innovation-induced changes in insurance demand also have greater innovation-induced changes in costs?

2.3 Changes in the Value of Insurance

Next, I consider changes in the value of insurance as technology changes. I consider two cases. First, I show how technological change influences the value of insurance in a world with no selection (i.e., insurance prices remain individual-specific and actuarially fair). Second, I consider a case where technological change generates selection and insurance prices respond.

Technological Change with No Selection. I first consider a case where there is technological change but no efficiency loss from selection; individuals face prices that are equal to their expected costs. We can write the change in the value of insurance as:

$$\frac{E[u_{i,k}^{I*}] - E[u_{i,k}^{U*}]}{u'} - \frac{E[u_{i,g}^{I*}] - E[u_{i,g}^{U*}]}{u'} = \frac{1}{2}\frac{-u''}{u'}m_k^2\pi(1-\pi) - \frac{1}{2}\frac{-u''}{u'}m_g^2\pi(1-\pi)$$

$$\Delta V_I^{NS} = \underbrace{\frac{1}{2}\frac{-u''}{u'}}_{>0}\left[\underbrace{m_k^2\pi(1-\pi) - m_g^2\pi(1-\pi)}_{>0}\right] > 0 \tag{3}$$

The first term is positive because the utility function is concave. The effect of technological change appears in the second term, which is also positive.[6] Because innovation increases the variance of medical spending, it increases the value of insurance.

Technological Change with Selection. Next, I consider how technological change affects the value of insurance when there is adverse selection. The key distinction in the world with selection is that prices are no longer equal to individual-specific marginal cost. Instead, they are set according to plans' average costs, which are weakly greater than marginal costs in a market with adverse selection.[7]

How does technological change influence insurance value when there is selection? Using the more general formula for the value of insurance derived in Appendix B.1, we can write the change from technology g to technology k as:

$$\Delta V_I^S = \underbrace{\left[(p_k - m_k\pi) + \frac{1}{2}\frac{-u''}{u'}(p_k^2 + m_k^2\pi - 2p_k m_k\pi)\right]}_{\text{value of insurance, technology } k\text{, with selection}} - \underbrace{\left[(p_g - m_g\pi) + \frac{1}{2}\frac{-u''}{u'}(p_g^2 + m_g^2\pi - 2p_g m_g\pi)\right]}_{\text{value of insurance, technology } g\text{, with selection}}$$

Note that $p_k - m_k\pi$ (and analogously, $p_g - m_g\pi$) is the selection wedge under technology k. This is the gap between individual-specific marginal costs ($m_k\pi$) and average costs (p_k in a world with selection) in equilibrium, and it is positive in a market with adverse selection. Denote the

[6] Note that this is positive by the assumption that $m_k > m_g$. In some cases, it is possible that new medical technologies may reduce spending, but for many of the high-cost technologies considered in this paper, this is a natural assumption.

[7] Formally, $p_S = E[C_i \mid \tilde{s} \leq s] \geq E[C_i \mid \tilde{s} = s] = p_{NS}$, where p_S is the price in a world with selection and p_{NS} is the price is in a world with no selection.

selection wedge in technology regime r as $\theta_r \equiv p_r - m_r\pi$. Collecting terms, we can write:

$$\Delta V_I^S = \underbrace{(\theta_k - \theta_g)}_{\Delta \text{ sel. wedge}} + \frac{1}{2}\frac{-u''}{u'}\left[(p_k^2 - p_g^2) + (m_k^2\pi - m_g^2\pi) - (2p_k m_k\pi - 2p_g m_g\pi)\right] \tag{4}$$

The effect of selection on the value of insurance $\Delta IV = \Delta V_I^{NS} - \Delta V_I^S$ is given by taking differences between Equations 3 and 4. Doing so and rearranging terms yields an expression for the change in insurance value ΔIV:

$$\Delta IV = \Delta V_I^{NS} - \underbrace{\Delta\theta}_{\substack{\text{(1) wedge} \\ \Delta\ (>0)}} - \frac{1}{2}\frac{-u''}{u'}\left[\underbrace{(p_k^2 - p_g^2)}_{\substack{\text{(2) price} \\ \Delta\ (>0)}} + \underbrace{\pi(m_k^2 - m_g^2)}_{\substack{\text{(3) med. spend} \\ \Delta\ (>0)}} - 2\pi(p_k m_k - p_g m_g)\right] \tag{5}$$

With selection, the value of insurance changes according to a few terms. The selection wedge enters negatively (Term 1). The equilibrium gap between average and marginal costs reduces the value of insurance, as it drives prices higher than the efficient level. The decline in the value of insurance is increasing in the price difference between the pre- and post-innovation worlds (Term 2) and in the spending difference (Term 3). Intuitively, the selection-induced losses in insurance value are greater for (1) larger price distortions (i.e., greater $p_k^2 - p_g^2$) and (2) larger innovation-induced changes in spending risk (i.e., greater $m_k^2 - m_g^2$).

2.4 Changes in Welfare

A key implication of Equation 5 is that the wedge between average and marginal costs in equilibrium is an important factor in the change in the value of insurance as innovation changes. In this section, I provide graphical intuition for how this wedge may change – and consider how those changes may affect welfare – using a stylized version of the graph-theoretic framework of Einav et al. (2010). Let $s \in [0, 1]$ be the fraction of individuals in the market with insurance, with individuals arrayed on the x-axis in order of declining willingness to pay for insurance V. In Figure 1, the welfare costs of selection are governed by the demand curves (V), the average cost curves $AC = E[C_i|V_i \geq V]$, and the marginal cost curves $MC = E[C_i|V_i = V]$. Insurers set a uniform, breakeven price based on average costs, and the equilibrium price p_{eqm} and allocation s^*_{eqm} are

determined by the intersection of average costs and incremental demand.[8] The *efficient* allocation s^*_{eff}, however, is determined by the intersection of demand and marginal costs. Uniform pricing – which arises because insurers either do not know individuals' true marginal costs or cannot vary prices on the basis of those costs – distorts the equilibrium away from the efficient allocation. This creates the deadweight loss triangle shaded in gray, which is made up of individuals for whom it would have been efficient to purchase insurance (because $V_i \geq MC_i$) but who do not because of the uniform price ($V_i < AC$). This distortion also creates the selection wedge between average and marginal costs in equilibrium.

In this stylized example, Panel A shows that in the world with technology g there is modest adverse selection with a relatively small wedge between average and marginal costs in equilibrium. When technology changes, there are two effects: (1) the marginal cost curve MC rotates and becomes steeper (selection increases) and (2) the demand curve V rotates. The rotation of the two curves generates a new equilibrium price p^k_{eqm} and allocation s^k_{eqm}. The steepening of these two curves increases the deadweight loss from selection, as increased selection distorts the equilibrium allocation further from the efficient allocation than in Panel A, and increases the size of the equilibrium selection wedge. As a result of the selection, the equilibrium price of insurance rises from p^g_{eqm} to p^k_{eqm}.

This stylized example implicitly assumes that technological change increases adverse selection. However, in practice the effect of technological change on selection and welfare is ambiguous and will depend on the terms in Equation 2. Thus, I turn to a series of empirical exercises to estimate the effects of technological change on insurance markets in practice.

3 Setting and Data

3.1 Institutional Background: Medicare Part D

My empirical setting is Medicare Part D, the prescription drug insurance program for the elderly in the United States. Individuals who enroll in Part D plans largely enroll in one of two types of plans: standalone prescription drug plans (PDPs) or Medicare Advantage prescription drug

[8] The setup assumes perfect competition, but it is straightforward to modify the framework for other market structures. See, e.g., Mahoney and Weyl (2017).

plans (MA-PDs).[9] MA-PDs integrate prescription drug coverage with coverage for other types of medical care (e.g., hospital care, outpatient services, etc.). I focus on PDPs, which enrolled more than 22 million people in 2024 and accounted for about 43% of all Part D enrollment (Cubanski and Damico, 2024). Individuals who enroll in a PDP do so during an open enrollment window that lasts from October to December each year, with the selected coverage beginning on January 1 of the following year.

The standard benefit design in Part D is complex and has changed over time. For clarity, consider the standard benefit in 2013, a year in the middle of my analytic sample. Individuals owe a deductible ($325 in 2013), after which they enter an initial coverage phase in which plans are responsible for 75% of total drug costs and enrollees the remaining 25%. Once beneficiaries reach the initial coverage limit ($2,970 total spending in 2013), they enter the coverage gap, where they are responsible for a greater share of their costs (47.5% for brand name drugs, 79% for generic drugs in 2013). Finally, individuals reach the catastrophic coverage threshold ($6,955 in 2013), after which they owe 5% of all remaining costs (Hoadley et al., 2013). There is no out-of-pocket maximum during the period that I study. Part D plans that offer this statutorily mandated benefit are classified as basic plans, while those that offer any kind of additional benefit (e.g., lower deductibles, higher initial coverage limits) are considered enhanced (*An Overview of the Medicare Part D Prescription Drug Benefit*, 2023).

Because the coverage gap exposes individuals to large out-of-pocket costs, providing additional coverage in this phase of the benefit is a particularly important source of plan differentiation in this market. Moreover, the coverage gap itself has been the subject of considerable policy debate over time. From 2006-2010, beneficiaries owed 100% of drug costs in the coverage gap, per the design of the Part D benefit. In 2011, provisions of the Affordable Care Act (ACA) intended to close the coverage gap over time began to kick in, requiring manufacturers to provide a 50% discount on brand name drugs in the coverage gap and plans to start paying a small fraction of generic drug costs in the gap. In 2013, insurers were required to start paying a fraction of brand name drug costs in the gap, and that fraction increased steadily over time from 2.5% in 2013 to 15% in 2018 (*Explaining Health Reform: Key Changes to the Medicare Part D Drug Benefit Coverage Gap*, 2010).

[9] Some eligible individuals enroll in prescription drug coverage via retiree plans or special need plans in Medicare. I do not focus on these types of plans in my analysis.

A policy similarly designed to reduce beneficiaries' out-of-pocket costs began in 2014, reducing the growth rate of the thresholds at which beneficiaries reached the coverage gap and catastrophic phase of the benefit (Cubanski et al., 2018). I discuss these policies and their relationship to my identification strategy in more detail in Section 4.2 and in Appendix D.

3.2 Sources of Data

I draw on a variety of data sources to conduct my analyses. First, I use Medicare administrative data that includes rich detail on both individuals and Part D plans. Second, I collect public data from the Food and Drug Administration (FDA) on new drug approvals in each year of my sample period (2010-2018). Third, I use public plan payment data from the Centers for Medicare and Medicaid Services (CMS) that captures plans' average Part D risk score, reinsurance payments received, and direct subsidy payments.

3.2.1 Medicare Beneficiary Level Data

I construct an analytic dataset at the beneficiary-year level. I begin with the Master Beneficiary Summary File (MBSF) Base File, which contains observations at the beneficiary-year level. The MBSF Base includes the universe of Medicare beneficiaries in a given year, regardless of their enrollment in Traditional Medicare or Medicare Advantage (MA), and includes various beneficiary characteristics. The MBSF also includes each beneficiary's Part D plan choice in a given year, allowing me to trace out enrollment over time for a given individual. For each year, I assign a beneficiary their Part D plan as of January of the calendar year, as this plan reflects their choice from the preceding months' open enrollment period. I combine the Base File with the MBSF Chronic Conditions and Other Chronic Conditions files. These files detail whether a beneficiary has any of 62 chronic conditions in a given year.[10]

I then combine the MBSF with various claims datasets that document beneficiaries' use of medical care and prescription drugs. First, I use the outpatient, inpatient, and Carrier files to construct indicators for various conditions that are either not included in the MBSF chronic conditions files

[10]These conditions include diagnoses such as Alzheimer's Disease and related dementias, congestive heart failures, diabetes, and others. For a complete list of the chronic conditions measured in these datasets, please see here: https://resdac.org/cms-data/files/mbsf-base

or lack relevant detail.[11] To do so, I use diagnosis codes recorded in individuals' medical claims. Second, I use prescription drug claims from the Part D Event (PDE) file covering a 20% sample of beneficiaries. Each observation in the PDE file is a prescription drug fill. I use the PDE to compute the total cost to the plan of covering a beneficiary in a given year, as well as the beneficiary's total out-of-pocket cost. I discuss the construction of these measures of cost in more detail in Appendix C.1.

3.2.2 Medicare Plan Level Data

Second, I construct a plan-year level analytic dataset using detailed Medicare data on Part D plans. I draw on several files for my plan level analyses. I begin with the Part D Plan Characteristics File, which includes detailed information on various dimensions of plan design, including benefit type (enhanced or basic), cost-sharing rules, plan service area, plan premiums, and the plan's formulary ID. The Formulary File includes formulary-drug-year observations that detail the drugs included in the formulary, the tier of the formulary to which a given drug belongs, and indicators for the use of various utilization management tools for a given drug such as prior authorization or step therapy.

The Plan Characteristics and Formulary Files allow me to observe whether a plan covers a given drug in a given year, the tier of the plan's formulary to which the drug belongs, and the utilization restrictions placed on the drug. I combine these datasets with the Cost-Sharing Tier Subfile to characterize plans based on their generosity for new drugs. The Cost-Sharing Tier Subfile contains plan-year-formulary tier level observations detailing cost-sharing rules for each tier on the formulary, such as whether the plan offers gap coverage. By combining the Plan Characteristics, Formulary, and Cost-Sharing Tier files, I observe each plan's tier choice for a given drug in a given year, along with the plan's cost-sharing rules for that tier, allowing me to characterize whether plans offer additional coverage for a given drug in the coverage gap.[12]

[11] For example, the MBSF Chronic Conditions file includes a flag for diabetes, but does not distinguish between Type 1 and Type 2 diabetes. For the purposes of understanding which drugs are relevant to which beneficiaries, however, the distinction is important, and I therefore use the claims to identify the two types separately.

[12] Note that this is not drug-specific additional coverage in the coverage gap, but rather tier-specific additional coverage, which will apply to a given drug based on how it is tiered by the plan.

3.2.3 Public Data Sources

I supplement the administrative data with public data from a variety of sources. First, I use the Food and Drug Administration's (FDA) Drug Approval Reports by Month data to compile a list of newly approved drugs in each year.[13] These data include a variety of different applications to the FDA. I focus on approvals for New Molecular Entities (NMEs) and biologic license agreements (BLAs) and link these data to the Medicare administrative data using the brand name of the drugs. Second, I use public Part D plan payment data from the Centers for Medicare and Medicaid Services (CMS) to measure the average risk of different plans' enrollees.[14] These allow me to observe the average Part D risk score of a plan's enrollees, average reinsurance payments to the plan per member per month, and average direct subsidy payment per member per month.

3.3 Sample Construction

I impose a variety of sample restrictions to construct two primary analytic samples, one at the beneficiary level and one at the plan level. First, I limit my beneficiary sample to individuals aged 65-99 who are continuously enrolled in Parts A, B, and D of Medicare in a given year (i.e., have 12 months of coverage). I then exclude individuals who enroll in Medicare Advantage at any point in the year, and, for my reduced form analyses, I exclude individuals who are eligible for the Part D low-income subsidy (LIS) program. I drop Medicare Advantage beneficiaries because I lack claims information for them, making it difficult to provide a full characterization of their health. For the reduced form analyses, I drop LIS beneficiaries because they face subsidized premiums for their prescription drug plans.[15] I further restrict the sample to individuals who appear in the 20% sample of the Medicare claims files, and I restrict the years of the analysis to 2010-2018.

Table 1 shows summary statistics for the beneficiary level and plan level analytic samples for the full sample (column 1) and then broken out by plan types. Panel A shows beneficiary characteristics. Beneficiaries enrolled in high coverage plans are slightly older, more likely to be non-Hispanic white, and, as expected, are sicker on average than beneficiaries enrolled in low coverage plans. Panel B shows characteristics of the plans. High coverage plans have fewer enrollees,

[13] These data are available here: https://www.accessdata.fda.gov/scripts/cder/daf/index.cfm.
[14] These data can be found here: https://www.cms.gov/medicare/health-drug-plans/plan-payment-data.
[15] In the structural estimation that I outline in Section 6, I keep LIS beneficiaries in the sample and use price variation created by these subsidies to identify the premium coefficients in my plan choice model.

but enroll sicker beneficiaries as measured by their Part D risk score and have about $1,000 more in spending per enrollee than low coverage plans. Notably, nearly all plans nominally covered the 2013-2014 drugs (i.e., included them in their formularies). However, as is clear in the table, all plans also used some kind of prior authorization on at least one of the drugs from the cohort. I return to this point below in my discussion of plan differentiation in this market.

4 Empirical Strategy

4.1 2013-2014 Innovation Shock

To estimate the causal effect of technological change, I study a natural experiment that occurred in the middle of my sample period. In 2013 and 2014, a wave of new prescription drugs hit the market that sharply increased the fraction of plan spending going to new drugs. Foremost among these drugs, in terms of press coverage, were Sovaldi and Harvoni, cures for Hepatitis C that were priced at $84,000 and $94,500, respectively, and had a sizable impact on spending growth (Hoadley et al., 2016). Beyond these cures, these two years also saw the approval of Jardiance and Trulicity, two Type 2 diabetes drugs that by 2021 were among the top ten Part D drugs in terms of gross spending, and Pomalyst, a multiple myeloma drug that entered the market priced at approximately $150,000 per year and for which spending grew steadily through the 2010s (Cubanski and Neuman, 2023; Palmer, 2014; Cliff et al., 2023).

In total, the FDA approved 68 new drugs over these two years. Though the number of approvals was not unusual, the impact on plan spending was. Figure 2 shows the average fraction of PDP plan spending in year t on drugs approved in year $t-1$. I measure this spending using a one-year lag to account for the fact that some drugs are approved late in the calendar year. The fraction of total plan spending on drugs approved in the prior year is relatively flat in the early 2010s; new drugs account for about 1-2% of total plan spending in each year. In 2014 and 2015, the years corresponding to the 2013 and 2014 approval cohorts, the average fraction of plan spending on newly approved drugs roughly quadruples to 8-9%, before steadily falling back down.[16] These changes were not merely a blip, as spending on these two cohorts of new drugs remained high,

[16] A natural question is whether all of this change in spending reflects spending on new Hepatitis C cures. In Appendix Figure A1, I show that while Hepatitis C drugs are the primary drivers of new spending in 2014 and 2015, spending on other new drugs represents a sizable fraction of the new drug spending in each year.

reaching 12.7% of all Part D spending in 2023.

The sharp change in the costliness of new drugs provides useful time series variation for understanding the effects of high-cost technological change on insurance markets. I combine this time series variation with cross-sectional variation in plans' exposure to the innovation shock to identify the causal effect of the shock on various outcomes. I define a plan as "treated" by the innovation shock if it offered gap coverage for at least one of the 2013-2014 drugs in the years 2013 or 2014, the onset of the innovation shock.[17] I compare these treated plans to a set of control plans that never offer gap coverage for any of the 2013-2014 drugs at any point in the sample period. I refer to the treated plans as "high coverage" plans throughout the remainder of the paper, and I refer to the control plans as "low coverage" plans. Notably, the low coverage plans in this setup may still offer other types of enhanced coverage (e.g., lower deductibles, reduced cost-sharing in the initial coverage phase, etc.).[18]

A natural question is why gap coverage for these new drugs should be the means for defining treatment, as opposed to plans' decision to cover the drugs at all or to apply some kind of utilization management like prior authorization. There are two reasons that I take the approach described here. First, as is clear in Table 1, there is very little differentiation across plans in terms of nominal coverage choices (i.e., inclusion of the new drugs in the formulary) or the use of prior authorization. Virtually all plans cover the drugs, and all of the plans that do use prior authorization. In general, plans do not appear to differentiate themselves from one another along these margins.

Second, gap coverage is both (1) financially consequential and (2) highly salient to consumers because of its effect on expected out-of-pocket costs. To underscore the first point further, Table 2 shows the average patient liability per fill for beneficiaries in the full sample (column 1), in the high coverage plans (column 2), and in the low coverage plans (column 3). For the average fill, beneficiaries in the high coverage plans save approximately $140 relative to their counterparts in the low coverage plans.[19] The differences between high coverage and low coverage plans become

[17] In practice, some plans begin offering gap coverage for the drugs later in the sample period, and I drop these "later treated" observations from the sample in order to avoid contaminating my estimates.

[18] I make use of this fact in my reduced form analysis, using enhanced plans without additional gap coverage for the 2013-2014 drugs as controls in some specifications in order to rule out secular trends affecting the market for enhanced coverage and use a set of similarly generous plans as controls.

[19] Note that this is on a per fill basis, so for medications that need to be refilled regularly, even this overall average amounts to a considerable amount of money per year.

even more stark when focusing on high-cost drugs. For drugs whose overall average patient liability (i.e., average across all plans) is in the top quartile of the distribution, beneficiaries in high coverage plans save approximately $400 per fill. For drugs in the top 10% of the distribution, beneficiaries in high coverage plans save nearly $1,100 per fill. From a patient perspective, the financial differences between the high and low coverage plans are quite large.

Patients' out-of-pocket costs are also relatively salient in this setting. Medicare provides a Plan Finder tool that allows individuals to enter the bundle of drugs they use, their ZIP code, and their preferred pharmacies before outputting an expected total out-of-pocket cost (premium plus cost-sharing) for each plan in their choice set (*CMS Has Implemented Processes to Oversee Plan Finder Pricing Accuracy and Improve Website Usability*, 2014). This heightens the salience of out-of-pocket spending relative to other dimensions of plan differentiation (e.g., prior authorization) that are difficult for beneficiaries to observe.

4.2 Causal Effects of Technological Change

I estimate the causal effect of technological change on costs and premiums for the high coverage plans using two-way fixed effects. Using the plan level dataset described in Section 3.3, I compare outcomes for the high coverage and low coverage plans using plan level event studies of the following form:

$$Y_{j,t} = \delta HighCov_j + \alpha_t + \sum_{t \neq 2012} \beta_t (\mathbf{1}[HighCov_j] \times \mathbf{1}[year_t = t]) + \gamma_m + \varepsilon_{j,t} \tag{6}$$

where $Y_{j,t}$ is the outcome of interest for plan j in year t; $HighCov_j$ is an indicator for whether plan j is high coverage; $\mathbf{1}[year_t = t]$ is an indicator for each year in the sample; α_t is a year fixed effect; γ_m is a PDP region (i.e., market) fixed effect; and $\varepsilon_{j,t}$ is an error term. The β_t coefficients on the interaction term capture changes in plan outcomes in the high coverage plans relative to low coverage plans in each year relative to 2012 (the omitted year). I weight regressions by plan enrollment and cluster standard errors at the plan level.

The key identifying assumption for this event study framework is that the low coverage plans represent a plausible counterfactual for how the high coverage plans would have evolved absent the innovation shock. The standard test for this assumption is to evaluate whether outcomes

between the two groups evolve in parallel in the years prior to the treatment (in this case, the innovation shock). If low coverage plans were evolving differently prior to the innovation shock, then they may not provide a good counterfactual for the high coverage plans in the post-innovation years, and the estimated treatment effects may be biased. I find little evidence of any pre-trend in my estimated event studies, as I discuss in more detail in Section 5.

A second concern is that there are coincident shocks that differentially affect the high coverage plans. If so, then these policies, rather than the innovation shock, may explain the estimated effects. A natural concern is that policy changes – for example, provisions of the Affordable Care Act (ACA) that went into effect around this time – played a role in changes in plan costs and premiums. In Appendix D, I provide a detailed discussion of policy changes affecting gap coverage at this time and how they relate to my identification strategy and outcomes. Competing ACA policies are unlikely to explain my results for a few reasons. In some cases, these policies do not bind for the high coverage plans. In others, the policies pre-date the innovation shock, allowing me to test for any differential effects in my pre-trends; I find none. Finally, the mechanical effects implied by the policies are too small to explain more than a small fraction of my estimated effects.

An important caveat to my empirical approach is that selection against high coverage plans will have spillovers on the low coverage plans, a violation of the Stable Unit Treatment Value Assumption (SUTVA). Given the considerably larger market share of the low coverage plans in this setting, the effects of marginal individuals' switching on the low coverage plans are likely small. My structural model in Section 6 allows me to account for these spillovers more directly.

5 The Effect of Technological Change on Insurance Markets

In this section, I present various pieces of reduced form evidence on the effects of technological change on insurance markets as motivated by the conceptual framework in Section 2.

5.1 Demand-Side Effects of Technological Change

I begin by estimating the effects of technological change on enrollee costs. Figure 3 shows the effect of the 2013-2014 innovation shock on insurers' average cost per enrollee. Panel A shows the raw data, plotting the mean average cost for the high coverage plans (green), low coverage plans

(blue), and the full market (black). Average costs costs are on very similar trends in the two types of plans prior to the innovation shock before they diverge when the 2013-2014 cohorts of drugs hit the market. Average costs for the high coverage plans increase sharply relative to low coverage plans and continue to do so for the remainder of the sample period. The near-symmetric decline in average costs for the low coverage plans in 2014, against the small upward trends in costs in the preceding years, suggests that selection may contribute to these patterns. Average costs for the full market remain relatively flat over this period.

In Panel B of Figure 3, I show the event study corresponding to the raw data, estimated according to Equation 6. There is a small pre-trend between the two groups of plans, but on the whole they exhibit similar patterns of costs prior to the innovation shock. In 2013, the year the shock arrives, there is a small but statistically significant increase in costs for high coverage plans. The small magnitude of the shock in this initial year is unsurprising, because the FDA approves drugs continuously over the course of the year, meaning that this year is only partially treated. From 2014 onward, all of the post-period coefficients are positive and significant, suggesting a sharp and significant increase in average costs for the high coverage plans. The difference-in-differences estimate of the cost increase is approximately $588, which amounts to approximately a 35% increase in insurers' costs over the pre-period mean. Risk-adjustment fails to offset this increase, as the shock increases risk-adjusted costs by $563 (Appendix Figure A2).

Motivated by these changes in cost, I conduct a series of analyses designed to assess whether these increases coincide with changes in the underlying risk of consumers in the high coverage and low coverage plans. I consider two measures of plans' risk. First, I use plans' average Part D risk scores, which capture changes in *measured* risk for plans. Second, I examine average reinsurance payments per member per month to each plan, which capture changes in *tail* risks.

In Appendix Figure A3, I show changes in average Part D risk scores. When examining all plans (Panels A and B), I find significant but small effects on plan risk; technological change increases the average Part D risk score in the high coverage plans by about 0.026 points (Table 4). When focusing on enhanced plans, however, I see clearer patterns of sorting. In this sample, technological change increases risk in the high coverage plans by .105 points (approximately 11%). This appears to be driven largely by a decline in the average risk of enrollees in the enhanced, low

coverage plans.[20] The average Part D risk score of the high coverage plans is fairly stable over the sample period. This is consistent with a pattern of intensive margin selection where those leaving the low coverage plans are high-risk relative to inframarginal enrollees in low coverage plans but similar in risk to inframarginal enrollees in the high coverage plans.

Second, I examine changes in average Part D reinsurance payments per enrollee per month to plans as a measure of tail risk (Appendix Figure A4). These payments capture the extent to which the federal government intercedes in order to protect plans financially for large expenses above the catastrophic threshold (Jung and Feldman, 2018). There is little systematic pre-trend in the years leading up to the innovation shock before a sharp increase in reinsurance payments to the high coverage plans. Reinsurance payments remain differentially high for the high coverage plans for several years following the shock before returning to similar levels by the end of the sample period. The difference-in-differences estimate of the effect is approximately $16 per month ($192 per year), a 68% increase over the baseline mean.

Both risk score and reinsurance compensate plans for enrolling sicker enrollees, thereby increasing plans' revenues and helpful to offset rising costs that may be induced by selection. However, as is clear from the point estimates above, the rise in payments to plans is small relative to the observed increases in costs: risk-adjusted costs for the plans rise by $563, and reinsurance payments increase by only $192 to cover this increase. In Section 5.3, I show that this translates into higher premiums in these high coverage plans.

Taken together, these estimates suggest large and meaningful effects of the innovation shock on demand-side outcomes. Technological change sharply increases average enrollee costs in the high coverage plans relative to low coverage plans. These cost changes coincide with meaningful increases in the average risk of high coverage plans relative to low coverage plans, and reinsurance payments to the high coverage plans rise to cover costs. Importantly, however, these cost increases could reflect a variety of factors, such as moral hazard, mechanical increases in plan spending, or adverse selection. Given that uncertainty, I next turn to a series of empirical exercises designed to disentangle these competing explanations.

[20] There is a small dip in average risk scores for all plans in 2014. This likely reflects an update to the the Rx-HCC algorithm used to compute individual risk scores that took place for the 2014 year. CMS recomputed risk scores based on updated data from the Part D event file and accounting for the small changes in plan liability (Centers for Medicare and Medicaid Services, 2013).

5.2 Disentangling Moral Hazard and Adverse Selection

Changes in plan costs could reflect various underlying channels. First, rising costs could reflect moral hazard spending in the high coverage plans induced by more generous coverage. Second, cost increases could reflect adverse selection if high coverage plans attract a changing set of enrollees. Finally, the changes in spending could be mechanical increases if individuals whose costs increase are disproportionately enrolled in the high coverage plans in the pre-innovation period.[21] In this section, I conduct a series of tests designed to disentangle these explanations.

I begin by decomposing changes in plan costs into spending on the new drugs versus spending on other drugs. If plans' costs are rising because generous coverage on the 2013-2014 drugs induces more utilization (moral hazard), then the cost effects should be driven by spending on those new drugs. To test this, I re-estimate Equation 6 separately for spending on the 2013-2014 cohorts of new drugs versus spending on all other drugs. High coverage plans do indeed see more spending on the 2013-2014 drugs following their approval, an increase on the order of approximately $30 per enrollee per year (Figure 4, Panel A). However, nearly 95% of the increase in plan costs comes from spending on *other* drugs (Figure 4, Panel B). Given the widespread use of prior authorization on these new drugs (see Table 1), it is not a surprise that plan spending on new drugs is limited. High coverage plans' costs are not simply rising because more generous coverage induces greater utilization of newly approved drugs among plan enrollees.

The fact that nearly all of the relative cost increase is attributable to spending on other drugs suggests that moral hazard is unlikely to explain changes in plan costs. Therefore, I consider an alternative explanation: that the underlying composition of beneficiaries in the high coverage plans is changing, and this influences high coverage plans' costs relative to the low coverage plans. To test this hypothesis, I follow the work of Shepard (2022) and examine beneficiary switching choices. In Figure 5, I plot outcomes for three groups of individuals: (1) those who switch into the high coverage plans (red), (2) those who switch out of the high coverage plans (green), and (3) stayers, who remain enrolled in the high coverage plans (blue).[22] In Panel A of Figure 5, I show the probability of using the 2013-2014 drugs for each group in each year. In the years following

[21] Note that this is a form of selection in and of itself in the sense that individuals with greater spending increases differentially sort into high coverage plans at baseline.

[22] I exclude all individuals who switch following the exit of their previous plan. Doing so allows me to rule out that switches are precipitated by plan exits, as opposed to the innovation shock.

the innovation shock, switchers into the high coverage plans are more likely than switchers out or stayers to use the new drugs. By 2016, the first year of plan choices after all 2013-2014 drugs are approved, the pattern is particularly striking: switchers in are approximately three times as likely to use the new drugs. Importantly, comparing the red and blue series allows me to examine the probability of new use *for individuals in the same type of plan*, which rules out the possibility that greater use among switchers in is due to differences in generosity of coverage.

The key selection challenge for plans is that these switchers in are disproportionately costly on multiple dimensions. In Panel B of Figure 5, I show average prior year costs for each group in each year. Prior to the innovation shock, spending is slightly higher among switchers but exhibits little systematic pattern. Following the approval of the new drugs, however, individuals switching into the high coverage plans are increasingly costly, with the previous year costs of switchers in diverging sharply from the previous year costs of those who remain enrolled in the high coverage plans. By 2016, those switching into the high coverage plans are nearly twice as costly as those who remain enrolled.

In Appendix Figure A5, I re-estimate these figures, restricting the sample only to individuals who switch to and from enhanced plans (i.e., from an enhanced low coverage plan to one of the high coverage plans, and vice versa). Doing so allows me not only to test the robustness of the original switching estimates, but also to provide more direct evidence on the switching patterns underlying changes in plan risk scores documented in Appendix Figure A3. I find that these patterns of selection are even more pronounced in this sample. This suggests that these plan switching results reflect selection not only from basic plans, but also more refined patterns of selection within different types of enhanced coverage. These findings are also consistent with the evidence in Appendix Figure A7 that innovation-induced cost increases are particularly sharp when examining enhanced plans.

All of these patterns are consistent with dynamic adverse selection. The innovation shock induces individuals aiming to use the 2013-2014 drugs to switch into the high coverage plans, as demonstrated by their much higher rates of use conditional on coverage type. Those switchers, however, are disproportionately high-cost on many dimensions. The natural question is how supply-side outcomes evolve in tandem with these demand-side results. I turn to this question now.

5.3 Supply-Side Responses

Standard models of dynamic adverse selection predict supply-side responses to these changes in costs and plan switching. As costs rise, plans are forced to raise premiums to avoid suffering losses. When these premium increases induce further switching out by low-cost individuals, a 'death spiral' can take place, leading to reductions in enrollment in the high coverage plans in equilibrium. I test these predictions using data on plan premiums, individual plan choices, and market shares over time.

As plan costs rise, so too do plan premiums. Figure 6 shows the effect of the innovation shock on monthly premiums, with the raw data plotted in Panel A and the corresponding event study shown in Panel B. As with costs, high coverage and low coverage plans trend similarly in the pre-innovation period before diverging sharply around the innovation shock. The pre-period coefficients are all statistically indistinguishable from zero, but are positive and significant throughout the post-period. The pooled difference-in-differences estimate of the effect of the innovation shock on premiums is an increase of $21 per month ($252 per year), approximately 52% of the pre-period mean.[23] Notably, the sharpest increases in premiums (as shown by the raw data) come in 2016, which is the first year for which premium bids were submitted after the full approval of the 2013-2014 drug cohorts.

These premium increases have important implications for the composition of beneficiaries enrolled in the high coverage plans. As premiums increase for the high coverage plans, individuals who switch out are increasingly low-cost relative to those who stay enrolled, as shown by the divergence between the green and blue series in Figure 5, Panel B. This is consistent with standard predictions of unraveling in a market with dynamic adverse selection. As plan premiums rise to cover increases in costs, price-sensitive low-cost enrollees leave the plans, driving average costs higher. In Appendix Figure A14, I provide further evidence for this point by plotting individuals' price sensitivity (from Equation 7) against their total costs (Panel A) and incremental costs (Panel B).[24] As is clear in the figure, price sensitivity is negatively correlated with costs, consistent with

[23] The timing of the changes is notable. Since Part D plan premium bids are submitted during the prior year, the small uptick in 2013 suggests a certain amount of anticipation on the part of insurers. This is not surprising as far as technological change is concerned. The results of Phase III clinical trials are published before formal FDA approval is granted, so insurers have some foresight about drugs that may be approved in a given year.

[24] I estimate individuals' price sensitivity using the plan choice model estimation discussed in Section 6.1.

the switching evidence in Panel B of Figure 5. The most price sensitive individuals in the market are also the least expensive to insure, suggesting adverse selection.

The final stage of this process of unraveling is a decline in the number of individuals enrolled in the high coverage plans. Thus, I next test whether technological change leads to a supply-side contraction of the high coverage plans' market share, consistent with the unraveling of generous coverage. In Figure 7, I plot the market share by year for the low coverage plans (blue) and the high coverage plans (green). I normalize each series by its pre-period mean so that the change from 2013-2018 can be interpreted as a percent change relative to 2010-2012. The figure shows substantial differences in the evolution of market share for the two types of plans. In the years leading up the innovation shock, the two types of plans trend generally similarly, though there is slightly more noise in the market share for the high coverage plans. At the onset of the innovation shock, however, there is a sharp and sustained decline in the market share of the high coverage plans. The difference-in-differences estimate of the effect of the innovation shock on the high coverage plans' market share is -0.49 (SE = 0.10), implying a 49% decline in enrollment in generous coverage.[25] This change is consistent with standard Akerlovian unraveling where higher costs beget higher prices, which in turn drive steadily more individuals out of enrollment in the high coverage plans.

Notably, this unraveling occurs despite the presence of risk-adjustment in the Part D program. There may be several explanations for this. The risk-adjustment formula may not be updated frequently enough, making it unable to capture changes in the costliness of individuals with certain conditions as new drugs are approved (Carey, 2017). Alternatively, new innovation may drive sorting conditional on CMS risk scores (Brown et al., 2014) or selection on moral hazard (Shepard, 2022). Understanding these shortcomings of the risk-adjustment model is an interesting avenue for future work.

Much of the literature on insurance and innovation has emphasized the importance of demand-side effects of innovation (Lakdawalla and Sood, 2009; Lakdawalla et al., 2017). These results underscore the importance of considering endogenous supply-side responses as well. As costs, risk, and selection increase, plans respond by raising prices. When they do, low-cost consumers switch

[25] In Appendix Figure A6, I show that these declines in market share coincide with a sharp decline in the number of high coverage plans in the market, as 56% of high coverage plans exit from 2013-2018, compared with just 25% among low coverage plans.

plans, driving average costs higher. Ultimately, the market share of the high coverage plans falls by approximately 49%, consistent with standard predictions of partial market unraveling. The sharp decline in high coverage plan enrollment, combined with concomitant increases in plan costs, risk, and switching patterns consistent with adverse selection, underscore the broader conceptual point: while technological change can make generous coverage more valuable, it may also make that coverage harder for the market to sustain.

5.4 Robustness

I conduct a series of robustness checks to further explore the identifying assumptions outlined in Section 4.2. First, I estimate a series of specification checks in order to rule out various alternative explanations for my results. These estimates are shown in Appendix Table A1. Columns (1) and (2) show the main difference-in-differences specification including issuer fixed effects. The estimates change very little; my cost and premium estimates are not driven by one large national insurer. Columns (3) and (4) show estimates with plan characteristics interacted with year indicators in order to account for differential patterns of costs and premiums by different plan characteristics. Column (3) includes an indicator for a plan belonging to a national PDP interacted with the year indicators, while column (4) does the same with an indicator for a plan being below the Part D premium benchmark. Again, I find very similar results. In columns (5)-(7), I include indicators for plan generosity in other phases of the Part D benefit – reduced cost-sharing, lower deductibles, and lower cost-sharing in the initial coverage phase – interacted with year indicators. These allow me to assess whether the observed results are driven by selection against other plan features besides gap coverage for the 2013-2014 drugs. Again, the results are qualitatively similar to my main estimates.

Next, I test the robustness of my main results to varying the comparison group. The results of these checks are shown in Appendix Table A2. First, I re-estimate Equation 6 restricting to a sample of plans that are classified in the Medicare data as enhanced. Enhanced plans may offer additional coverage on a variety of dimensions; some offer the additional gap coverage outlined above, while others offer lower deductibles or higher initial coverage limits. As a result, there is variation even among enhanced plans in additional coverage in the gap. Re-estimating these

results on the enhanced plans allows me to rule out secular trends that affect enhanced plans relative to basic plans more broadly, and compare the high coverage plans in my sample to a set of plans that also offer additional coverage, but on different parts of plan design.

The results for the enhanced-only sample reinforce the main results. Figure A7 shows the effect of the innovation shock on costs. As in the main specification, the plans are on relatively similar trends in the years immediately prior to the innovation shock, before the enhanced plans with gap coverage for the 2013-2014 drugs experience a sharp increase in costs relative to the enhanced plans without such coverage. The difference-in-differences estimate of the effect of the innovation shock on costs when focusing on the enhanced plans is $924. As noted in Section 5.1, I find particularly pronounced increases in average Part D risk score and reinsurance payments for this sample as well, suggesting large increases in plans' risk alongside increases in costs. As in the main results, premiums follow suit, rising in the high coverage plans by approximately $473 per year (Figure A8).[26] Taken together, these findings reinforce the main results, and provide evidence that secular trends affecting enhanced plans are not driving the main findings.

I also re-estimate my main results pertaining to costs and premiums using only a set of plans that are in the data at the start of the sample period (2010). The goal of this analysis is to rule out the possibility that the main results are driven by the entry of certain plans into the market. Figures A9 and A10 show the results, which are summarized in Columns (3) and (4) of Appendix Table A2. The point estimates for costs and premiums are quite similar to those estimated on the main sample of plans, suggesting that the main findings are unlikely to be the result of a few large plans entering the market.

6 Welfare and Selection Estimates

This section details my structural analysis. I estimate models of plan choice and plan costs to construct the empirical analogues of the demand and cost curves outlined in Section 2. I then use these curves to estimate changes in selection and welfare drawing on the frameworks outlined in Einav et al. (2010) and Hendren (2021).

[26] In 2010, the two plan types exhibit different premium patterns. However, this year precedes the innovation shock by several years, and the two groups of plans exhibit nearly identical trends in the remaining years leading up to the shock.

6.1 Demand Estimation

I begin by estimating plan demand, simplifying consumers' choices in two ways. First, I focus on the intensive margin of plan choice, modeling the decision of which plan to choose rather than the decision to purchase a plan at all. Second, I restrict the choice space and limit consumers to the choice of a high coverage plan (H) or low coverage plan (L).[27] In Appendix E.1, I discuss my construction of the choice model dataset in more detail. I model individual i's utility from plan type j at time t as:

$$U_{i,j,t} = \underbrace{\alpha(x_{i,t})Prem_{i,j,t}}_{\text{Price}} + \underbrace{\beta(x_{i,t})OOP_{i,j,t}}_{\text{Out-of-pocket}} + \underbrace{\delta(x_{i,t})Inertia_{i,j,t}}_{\text{Inertia}} + \underbrace{\tau_j}_{\text{Plan FE}} + \theta_{j,r,t} + \Gamma_{j,r,g} + \varepsilon_{i,j,t} \tag{7}$$

Utility for individual i from plan j depends on four plan features: (1) prices $Prem_{i,j,t}$, which are observed in the data and are measured net of rebates to the insurer and subsidies to individuals based on their low-income subsidy (LIS) status; (2) individuals' expected out-of-pocket (OOP) costs $OOP_{i,j,t}$ in plan j at time t; (3) an indicator for whether an enrollee is currently enrolled in a given plan in order to capture inertia (Handel, 2013); and (4) a plan fixed effect (τ_j) designed to capture unobserved, time-invariant differences in plan quality between L and H. I also include plan type-PDP region-year ($\theta_{j,r,t}$) and plan type-PDP region-LIS group ($\Gamma_{j,r,g}$) fixed effects for identification, as discussed below. $\varepsilon_{i,t}$ is an i.i.d., type-I extreme value error term. I allow the coefficients on price, out-of-pocket costs, and inertia to vary with a number of individual characteristics $x_{i,t}$: chronic conditions quintile, age cells, and LIS income group. I estimate the model by maximum likelihood using a random 10 percent random sample of both LIS and non-LIS beneficiaries, restricting to the 5 largest PDP regions.

Identifying Premium Coefficients. I identify premium coefficients using price variation created by Part D subsidy rules. In order to make PDPs more affordable, the Part D LIS program subsidizes premiums for individuals below 150% of the federal poverty level (FPL). Subsidy amounts are set regionally by CMS to make "benchmark" Part D plans in a given region free net of the subsidy, and individuals wishing to enroll in a more expensive, non-benchmark plan pay the

[27] These two restrictions are consistent with other work in this literature, such as Shepard (2022), who restricts attention to the intensive margin, and Finkelstein et al. (2019), who pool plans into analogous H and L groups.

difference between that plan's premium and regional benchmark (Wreschnig, 2023). During the sample period that I study, subsidies operated on a sliding scale. Individuals with income less than or equal to 135% FPL received the full premium subsidy; those with income 135-140% FPL received 75% of the subsidy; those with income 140-145% FPL received 50% of the subsidy; those with income 145-150% FPL received 25% of the subsidy; and those with income greater than 150% received no subsidy.

These subsidies generate price variation for different plan types across individuals within a region based on income. To use this price variation to identify the premium coefficients in my plan choice model, I include a rich set of fixed effects designed to absorb any price variation not due to these plausibly exogenous subsidies (Nevo, 2000; Shepard, 2022). I first include a set of plan type-region-year fixed effects. These fixed effects ensure that the price coefficients are identified only from differences in price for a given plan type (H versus L) across income groups within a PDP region in a given year. These price differences arise from the subsidies. Because there may be persistent differences in preferences across subsidy groups, I also include a set of plan type-region-LIS group fixed effects. These absorb any time-invariant differences in plan preferences across LIS groups within a given region. Net of these two sets of fixed effects, the premium coefficients are identified off of differential price changes for a given plan type, in a given region, across individuals of different subsidy groups. As others have noted, the intuition of this approach is akin to a difference-in-differences approach (Shepard, 2022).

6.2 Plan Cost Model

An important component of my selection analysis is estimating individuals' incremental marginal cost to the high coverage plans $\Delta MC_i = E[C_{i,H} - C_{i,L}]$. For this, I model costs C for individual i in plan type j at time t. I follow the approach of Jaffe and Shepard (2020) and Kong et al. (2024) to estimate these costs. I first construct an unbalanced panel of individuals in my main beneficiary sample who switch plan types exactly once between 2010 and 2018. I then estimate the following Poisson regression:

$$C_{i,j,t} = \exp(\alpha_i + \delta_t + \beta X_{i,t} + \theta_{j,r,p} + \varepsilon_{i,t}) \tag{8}$$

The key objects of interest are the plan type-region-period fixed effects $\theta_{j,r,p}$, which capture the causal cost effect of each plan type j in PDP region r in period p (pre- or post-innovation), conditional on individual fixed effects (α_i), year fixed effects (δ_t), and individual characteristics $X_{i,t}$ (5-year age bins, chronic conditions quintile, and PDP region of residence). I estimate separate regressions for the pre-innovation (pre-2013) and post-innovation (post-2013) periods to allow for the possibility that plan cost effects change with innovation. Following Kong et al. (2024), I construct the multiplicative effect of each plan as $\hat{\gamma}_{j,r,p} \equiv \exp(\hat{\theta}_{j,r,p})$ and compute an individual's predicted cost in counterfactual plan k as the product of their observed costs C_i and the ratio of the counterfactual and observed plan effects $\frac{\hat{\gamma}_{k,r,p}}{\hat{\gamma}_{j,r,p}}$.[28]

The key identifying assumption is that plan cost effects are identified off of within-person variation in costs that is observed when individuals switch plan types. As noted above, this is similar to other approaches in the literature that leverage enrollment in different plans over time for the same individual (Jaffe and Shepard, 2020; Kong et al., 2024). I also assume that plan effects on cost are proportional to underlying individual characteristics capturing risk (age, chronic conditions quintiles, etc.). Finally, as noted in Kong et al. (2024), the approach also assumes that the plan effects estimated on switchers can be extrapolated to the non-switching population.

6.3 Model Estimates and Fit

Appendix Table E1 shows the estimates from the plan choice model. Columns (1) and (2) show estimates and standard errors from a baseline model with no heterogeneity by individual characteristics, while columns (3) and (4) allow coefficients to vary by age and sickness (as measured by chronic conditions quintiles). The coefficient on plan premiums is negative across both specifications and for all groups and is similar to other estimates in this market (Abaluck and Gruber, 2011; Polyakova, 2016). Older and sicker individuals are less price sensitive, a result consistent with findings in other markets (Shepard, 2022).

Plan choice is relatively sensitive to out-of-pocket costs. However, as has been shown elsewhere, out-of-pocket sensitivity is considerably smaller than premium sensitivity (Abaluck and Gruber, 2011). As with premiums, older individuals are less sensitive to changes in out-of-pocket costs, though results are more mixed examining individual sickness. Inertia is a persistent force.

[28] For more details on the Kong et al. (2024) model of individual cost, please see Appendix E.2.

Following Shepard (2022) and converting the inertia coefficient to dollars by dividing it by the premium coefficient implies that switching costs in this market are approximately $95 per month.[29]

Appendix Figure E2 shows the distribution of plan cost effects estimated using Equation 8. Cost effects are generally larger than 1 for the high coverage plans (green) and generally smaller than 1 for the low coverage plans (blue), indicating that the high coverage plans tend to increase costs relative to the low coverage plans. Not all plan effect estimates for the high coverage plans are greater than 1, which is consistent with the fact that the plans are not strictly vertically differentiated, but rather are differentiated on their coverage *for a specific set of drugs*. The gap in plan cost effects is generally small but grows from the pre-innovation to post-innovation period. Following the innovation shock, the gap in the average plan effect doubles, and the distribution of effects becomes markedly wider. These findings indicate that estimating plan effects separately by period is important for capturing heterogeneity in plan effects over time.

To validate the model, I combine the cost estimates with the predicted shares from the demand model and evaluate how well the model predictions mirror my reduced form patterns, following the approach in Kong et al. (2024). I collapse the plan choice dataset to the plan type by PDP region by year level, weighting by the model-predicted shares to get predicted costs. I repeat the exercise weighting by individuals' observed choices to get observed costs. For each collapsed dataset, I then estimate Equation 6, and compare the estimates from the two event studies.[30] Appendix Figure E3 shows the event study estimates using observed costs and choices (black) and estimates using predicted costs and choices (purple). The two series are nearly identical, and the model predictions closely reflect the reduced form patterns described in Section 5. With the model estimates in hand, I next turn to quantifying changes in selection and estimating welfare.

6.4 Quantifying Changes in Selection

I begin by using the demand estimates to measure changes in selection against generous coverage directly. To do so, I first construct each individual's incremental willingness to pay (WTP) for greater risk protection in the H plans as:

[29] This is quite similar to other estimates of switching costs in Part D. For example, Polyakova (2016) estimates a switching cost of approximately $85 per month.

[30] Note that these event study estimates differ slightly from the estimates in Section 5, because the plan choice dataset uses a different sample of individuals. However, the general pattern is the same.

$$V_{i,t} = \frac{-1}{\alpha(x_{i,t})} \cdot [U(OOP_H; x_{i,t}) - U(OOP_L; x_{i,t})] \tag{9}$$

dividing by the inverse of the price coefficient so that $V_{i,t}$ is in dollars. These estimates of predicted WTP exclude plan dummies (i.e., hold unobserved differences across plans fixed over time) and inertia. I use these estimates of WTP to plot the empirical relationship between individuals' realized costs (observed in the data) and their quantile q of marginal WTP for better risk protection (derived from the model). Specifically, I plot $E[C_i \mid \tilde{q} = q]$ using local linear regression. For consistency with the graphical framework, I construct the quantiles so that smaller quantiles correspond to higher WTP. To summarize the change in selection, I compute the ratio of costs for those in the 10th quantile of incremental WTP and those in the 90th percentile of WTP. Higher ratios are indicative of more selection, as individuals with greater willingness to pay have greater costs than those with lower WTP.

To illustrate the importance of technological change for selection, I split the sample into two time periods: 2010-2012 (pre-innovation) and 2015-2018 (post-innovation). Figure 8 plots estimated relationship between cost and quantile of WTP. In the pre-innovation period (in purple), there is modest adverse selection in the market, indicated by the downward sloping relationship between cost and WTP. Individuals in the 10th quantile of WTP are 1.4 times more expensive to insure than those in the 90th quantile.

How does this relationship evolve as technology changes? The navy line shows the same relationship in the post-innovation period, focusing on 2015-2018 to exclude years where the new drugs are being continuously approved. In the post-innovation period, the extent of selection is much greater, reflected by the steepening of the relationship between cost and WTP. Following innovation, those in the 10th quantile of WTP are approximately 19 times more expensive to insure than those in the 90th quantile. Much of the increase appears to be driven by individuals with the greatest incremental WTP, as indicated by the rotation in the cost-WTP curve. This pattern is consistent with the graphical framework outlined in Section 2. Selection against the high coverage plans' more generous risk protection increases sharply in the years following the innovation shock. In Appendix Figure A11, I show that these patterns persist for individuals' incremental costs as well.

To provide further insight on changes in selection, I estimate the decomposition outlined in Equation 2. I restrict the sample to individuals who appear in the data in the pre-innovation period g (2010-2012) and post-innovation period k (2015-2018). I then use the model estimates of $V_{i,t}$ (Equation 9) and estimates of individual costs in the data to estimate the component parts of the decomposition. I compute the change in an individual's demand ΔV_i and cost ΔC_i as the difference in their average incremental willingness to pay and cost between the pre- and post-innovation periods.

In Figure 9, I plot the empirical analogues of each of the components of Equation 2. Each bar represents the percentage of the total change in selection, $\text{Cov}(V_i^k, C_i^k) - \text{Cov}(V_i^g, C_i^g)$, that is accounted for by a given component. The blue bar indicates that pre-innovation sorting plays an important role in selection, driving about 13% of the observed change. This phenomenon is consistent with the notion that sicker individuals – or those more likely to see cost increases in response to new innovation – are already enrolled in high coverage plans at baseline. I provide evidence for this channel on two dimensions. First, I show that pre-innovation (2010-2012) enrollment in the high coverage plans is higher among those who ultimately use new drugs; have Hepatitis C, Type 2 diabetes, or multiple myeloma[31]; or have more chronic conditions (Appendix Figure A12). Second, I show that individuals with greater pre-innovation willingness to pay for additional risk protection were also significantly more likely to use the new drugs following approval. Those in the top 5% of pre-innovation incremental willingness to pay are 43.7% more likely to ultimately use new drugs than those in the bottom 5% (Appendix Figure A13). These results suggest some baseline sorting into the high coverage plans based on individual sickness and future utilization, consistent with the results of the decomposition.

Adverse selection also plays an important role in the total change in selection, accounting for approximately 22% of the increase. Individuals who see larger increases in incremental demand for the high coverage plans are those with higher costs at baseline, consistent with the switching evidence presented in Section 5.2. The remaining 65% of the change in selection is accounted for by changes in the covariance between individuals' demand response (ΔV_i) and their change in costs (ΔC_i).

Taken together, these results offer empirical support for the conceptual framework outlined in

[31] I focus on these conditions because each saw costly, innovative therapies approved as part of the 2013-2014 cohorts.

Section 2. Selection against the generous risk protection provided by the H plans – as measured by the steepness of the cost-WTP curve – increases in the years following FDA approval of new prescription drugs in 2013-2014. Consistent with the graphical framework, the change in the slope of the curve is driven largely by higher costs among people with greater WTP, as depicted by the *rotating* cost curves in Figure 8. The covariance decomposition in Figure 9 emphasizes the particular importance of classical adverse selection in driving these patterns. These facts, combined with the reduced form evidence detailed in Section 5, suggest that selection increased substantially following the innovation shock in a manner consistent with with the model outlined in Section 2.

6.5 Welfare and Policy Counterfactuals

What are the welfare consequences of this selection and unraveling? In this section, I use the model estimates to derive demand and cost curves and use these to evaluate welfare under the observed equilibrium and counterfactual policy designs.

Demand and Cost Curves. I first use the model estimates to construct demand and cost curves. To construct incremental demand for H, I iterate over a set of relative prices of H $\Delta p \equiv p_H - p_L$ and use the model estimates to simulate each individual's enrollment choice at a given relative price. The resulting incremental demand curve $D(s)$ reflects the fraction $s \in [0, 1]$ of the market enrolled in H at a given relative price, where the lowest s values again correspond to the greatest demand for H. For each s, I then compute the incremental average cost of individuals enrolled in H as $\Delta AC(s) \equiv E[C_H \mid \tilde{s} \leq s] - E[C_L \mid \tilde{s} > s]$ and incremental marginal costs $\Delta MC(s) \equiv E[C_H - C_L \mid \tilde{s} = s]$ using the estimates from the plan cost model (Weyl and Veiga, 2017). I smooth the simulated cost curves using local polynomial regression and use these demand and cost curves to conduct the welfare analysis.

Equilibrium and Welfare Framework. I consider equilibrium allocations where plans earn zero profits, which occurs where the relative price of H is equal to incremental average costs $\Delta p(s) = \Delta AC(s)$ (Handel et al., 2015; Weyl and Veiga, 2017). I begin by taking a market surplus approach to welfare SS^{MS}, as in Einav et al. (2010):

$$SS^{MS} = \int_{s=0}^{s^*_{eqm}} [D(s) - MC(s)]ds$$

Market equilibrium s^*_{eqm} is determined by the intersection of incremental demand and incremental average cost (i.e., $D(s^*_{eqm}) = \Delta AC(s^*_{eqm})$). In this market surplus framework, welfare is determined by the extent to which individuals' incremental willingness to pay exceeds their incremental marginal cost. Selection distortions lead to welfare losses by driving the equilibrium enrollment share lower than what would be efficient, and there is a welfare loss from too few individuals being enrolled in H, as those on the margin instead enroll in L.

Note, however, that selection also distorts the price of coverage, increasing it over what would be paid at the efficient allocation. This leads to transfers across individuals, as those who remain enrolled in H (inframarginal enrollees) now pay higher prices than they would if more individuals were enrolled in H. As noted by Hendren (2021), these transfers, too, matter for welfare in an ex-ante sense. Thus, I conduct a second set of welfare analyses using the ex-ante framework outlined in Hendren (2021). Ex-ante welfare allows me to capture the full insurance value of coverage from "behind the veil of ignorance." This distinction is particularly pronounced for high-cost new medical technologies, because the amount of foregone insurance value is increasing in the size of the financial risk.

Ex-ante demand $W(s) = D(s) + EA(s)$ is an individual's incremental willingness to pay – from behind the veil of ignorance – to have a fraction s of the market enrolled in H and is comprised of two terms. The first term $D(s)$ is the market incremental demand curve for H derived using the simulation described above. The second term, $EA(s)$, reflects the ex-ante value individuals place on expanding the fraction s of individuals enrolled in H by a small amount ds (Hendren, 2021). This value comes from reductions in the price of H as more of the market enrolls.[32] I follow Hendren (2021) and construct ex-ante demand using the demand and cost curves described above, combined with an measure of risk aversion and an estimate of out-of-pocket differences across individuals in H and in L.[33] Ex-ante social surplus at the equilibrium share s^*_{eqm} is given by:

[32] $EA(s)$ captures the transfer from individuals in L (who pay higher prices for H) to individuals in H (who pay lower prices as more people enroll), scaled by the difference in marginal utilities for those in H and L. For more details, please see Hendren (2021).

[33] I follow Handel et al. (2015) and set the risk aversion parameter to 5×10^{-4}. To compute the out-of-pocket difference, I use the estimates from the structural model capturing individuals' expected out-of-pocket costs in H and L

$$SS^{EA} = \int_{s=0}^{s^*_{eqm}} [W(s) - MC(s)]ds$$

Social surplus in the ex-ante framework depends on the extent to which ex-ante demand exceeds marginal costs, rather than the observed market demand. Using the two welfare frameworks, I estimate the welfare losses from reduced insurance value by comparing the social surplus achieved in equilibrium to the social surplus that would be attained at the efficient allocation. I start by considering an efficient allocation in a market surplus sense (where market incremental demand intersects incremental marginal cost) and then in an ex-ante sense (where ex-ante demand intersects incremental marginal cost).

Welfare Analysis and Counterfactuals. I use the simulated demand and cost curves to consider the welfare consequences of the selection described above. First, I examine the pre-post change in welfare in the market for high coverage plans in order to quantify the losses associated with selection. To do so, I simulate demand and cost curves separately in the pre-innovation (2010-2012) and post-innovation (2015-2018) periods and estimate welfare separately in each period.

Second, I simulate two counterfactual policy changes to the Part D program and examine how they influence enrollment, prices, and welfare. In the first counterfactual, I model the effects of a policy reducing government reinsurance payments to plans. Specifically, I reduce the government share of spending above the catastrophic spending threshold from 80% to 20%; increase the plan share from 15% to 80%; and reduce the beneficiary share to 0%. I recompute costs (both to individuals and to the plans) under this alternative set of rules and then re-simulate demand and cost curves to evaluate the welfare consequences of such a policy.

In the second counterfactual, I examine the effects of implementing perfect risk adjustment in the Part D market. I use the estimates from the plan cost model and construct a risk score $r_i = \frac{C_{i,L}}{\bar{C}_L}$ for each individual i based on their predicted L plan costs. I then compute risk-adjusted costs by dividing by this risk score. These risk-adjusted costs are identical across individuals in L but allow

described in Appendix E.1. In short, these capture expected differences in out-of-pocket costs across plans, holding fixed individuals' deciles of days supply, total drug spending, and total number of fills. This approach approximates the empirical object described in Hendren (2021) that captures differences in out-of-pocket costs between plan types that would occur if all individuals chose their level of utilization as though they were in H.

for moral hazard among individuals enrolled in H.

Results. Table 5 summarizes characteristics of the equilibrium allocation under different scenarios.[34] Columns (1) and (2) show equilibrium enrollment and the relative price of H. Columns (3) and (4) show the percent of the efficient consumer and social surplus achieved by the equilibrium under a market surplus definition of welfare. Columns (5) and (6) show the same using an ex-ante definition.

Panel A shows outcomes in the pre- and post-innovation periods. In the estimated pre-innovation equilibrium, about 22% of the market is enrolled in high coverage plans, slightly higher than the observed enrollment in the data. There is modest adverse selection in the market, as the equilibrium allocation achieves approximately 90% of the social surplus of the efficient allocation using a market surplus definition of welfare. Consistent with the model in Section 2, this distortion worsens in the years following the innovation shock. As shown in Appendix Figure A15, Panel B, the demand and cost curves rotate, with the slope steepening especially for costs. Following the innovation shock, the equilibrium fraction of individuals enrolled in the high coverage plans falls to 6%, and the equilibrium price of such coverage more than doubles. The equilibrium allocation achieves 57% of the social surplus that would be achieved at the efficient allocation under a market surplus definition of welfare. Selection reduces the value of insurance substantially in the post-innovation period.

Column (6) underscores the importance of the ex-ante approach to welfare in assessing the losses in the insurance value. While the lost insurance value is substantial in a market surplus sense, the effects are magnified considerably using an ex-ante approach to welfare, as the post-innovation equilibrium allocation achieves just 19% of the social surplus that would be achieved at the ex-ante efficient allocation of coverage. The higher prices paid by individuals who remain enrolled in the generous plans – in addition to the inefficiently low enrollment among people on the margin – play a sizable role in driving losses in insurance value.

In Panel B of Table 5, I consider how policies designed to combat selection affect equilibrium in this market. I first consider a policy to reduce the generosity of reinsurance. Reducing reinsurance payments increases the equilibrium relative price of generous coverage to nearly $235 per

[34]The corresponding demand and cost curves are shown in Appendix Figures A15 and A16.

month in the post-innovation period. As a result, the fraction of the market in generous coverage falls still further to 1.6%, and the equilibrium allocation achieves just 8% of the ex-ante efficient social surplus. With less generous reinsurance backstops, the market nearly unravels completely. Risk adjustment is similarly valuable for sustaining the market for high coverage plans. With improved risk adjustment, nearly 36% of the market enrolls in H, and the relative price of coverage falls to $25 per month. Taken together, these counterfactuals underscore the potential of policies such as reinsurance and risk adjustment to help stabilize insurance markets in the presence of technological change.

7 Conclusion

High-cost new medical innovation continues to accelerate, bringing with it a host of promising clinical benefits for patients. Given the expensive nature of these innovations, an important question is how insurance markets will evolve with this kind of technological change. In this paper, I highlight a key conceptual trade-off fundamental to this question: while new medical innovation increases the value of generous coverage, it may simultaneously make that coverage more difficult to sustain if it generates adverse selection.

I examine this trade-off empirically in Medicare Part D, the federal prescription drug insurance program for the elderly. I show that a plausibly exogenous innovation shock in the mid-2010s – driven by a wave of new medications for conditions such as Hepatitis C, Type 2 diabetes, and different cancers – substantially increased costs for a set of Part D plans offering generous coverage for these new drugs. The increases coincide with a changing selection of consumers in these high coverage plans, as individuals who switch in are disproportionately likely to use new drugs and disproportionately expensive to insure. In response, the affected plans raise their prices, and low-cost individuals switch out. The result is a partial death spiral of this particular form of generous coverage: the high coverage plans' market share falls by 49%.

This unraveling substantially reduces the insurance value of generous coverage. Following the innovation shock, equilibrium enrollment falls sharply, prices rise, and the equilibrium allocation of coverage achieves just 19% of the social surplus attained at the ex-ante efficient coverage level. These losses in insurance value accrue not only because of inefficiently low enrollment in

the high coverage plans but also because selection drives the price of these plans higher for those who remain enrolled. While these losses are large, the generous Part D reinsurance infrastructure prevents the market from unraveling completely. Weakening this reinsurance infrastructure leads to a near total death spiral, while more robust risk adjustment can sustain a higher level of equilibrium enrollment and a lower price.

These results have important implications for health insurance markets beyond the setting I study here. Indeed, given that I observe this degree of unraveling in a market that is heavily subsidized by the federal government, the consequences of technological change may be even starker in settings where policies to combat selection (e.g., risk adjustment or reinsurance) are less complete. Future work should examine these settings in order to understand how differently (or similarly) they fare in the face of technological change.

Ultimately, this work underscores the challenges that new innovations pose to insurance markets. The landscape of new prescription drugs, in particular, has changed dramatically in recent years with the advent of weight-loss drugs such as Ozempic and Wegovy. Breakthrough therapies for other conditions, such as Type 1 diabetes, may be on the horizon (Kolata, 2021). As new medical innovation continues apace, the value of health insurance will continue to grow, but, as I show here, existing policies for shoring up these markets may be insufficient to deal with this technological change. How best to build on these policy remedies and stabilize these markets for the innovations to come is an important avenue for future work.

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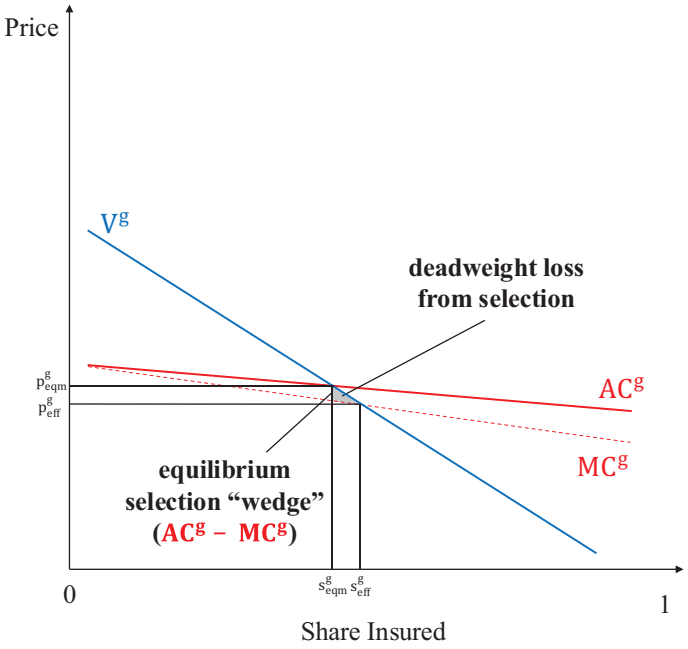
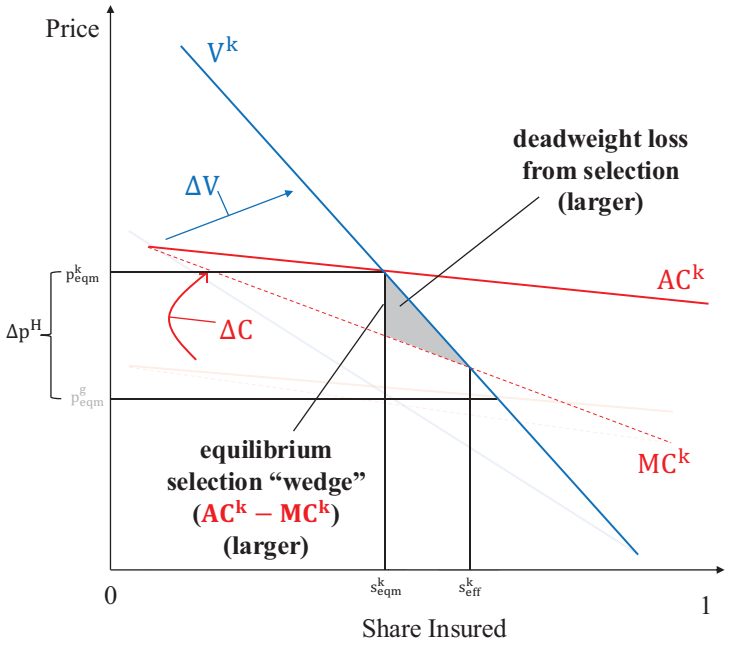
Figures

Figure 1. Graphical Model of Adverse Selection and Technological Change

(A) Technology g

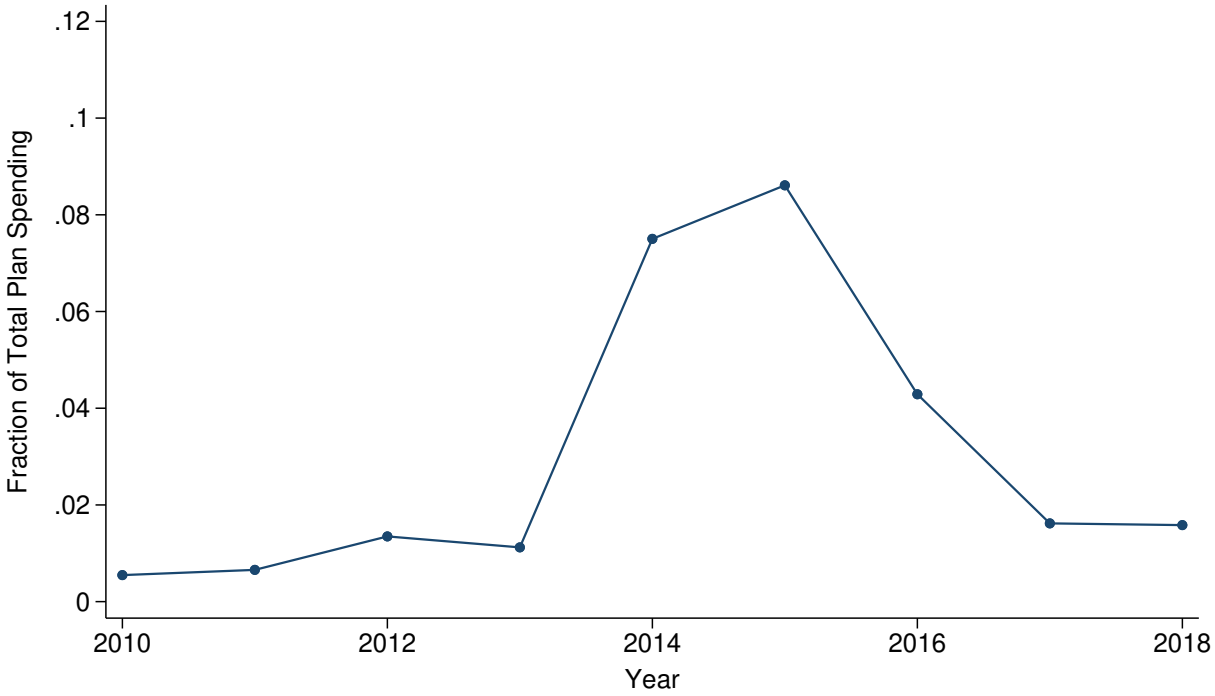


(B) Technology Changes to k



Notes: Figures illustrate the theoretical effect of technological change on an insurance market. In both figures, individuals are arrayed on the x-axis in decreasing order of insurance demand V. In Panel A, medical technology is g, and there is modest adverse selection indicated by the downward sloping marginal cost curve. In Panel B, medical technology changes to k and the incremental demand curve V rotates, as do the cost curves. Selection steepens, as MC^k is steeper than MC^g, and the equilibrium price of coverage increases.

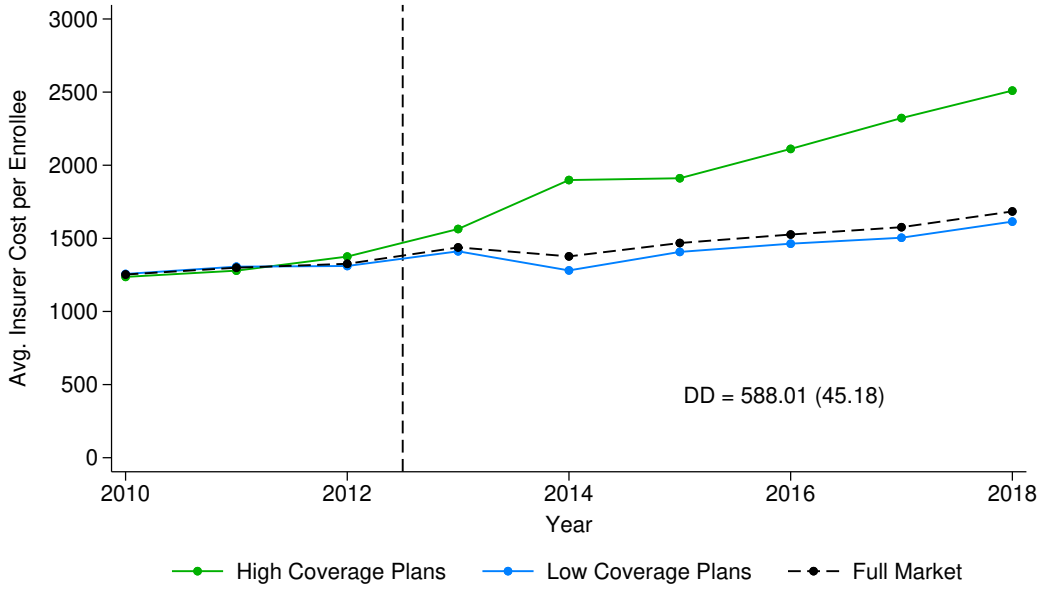
Figure 2. Fraction of Total Plan Spending on Drugs Approved Previous Year



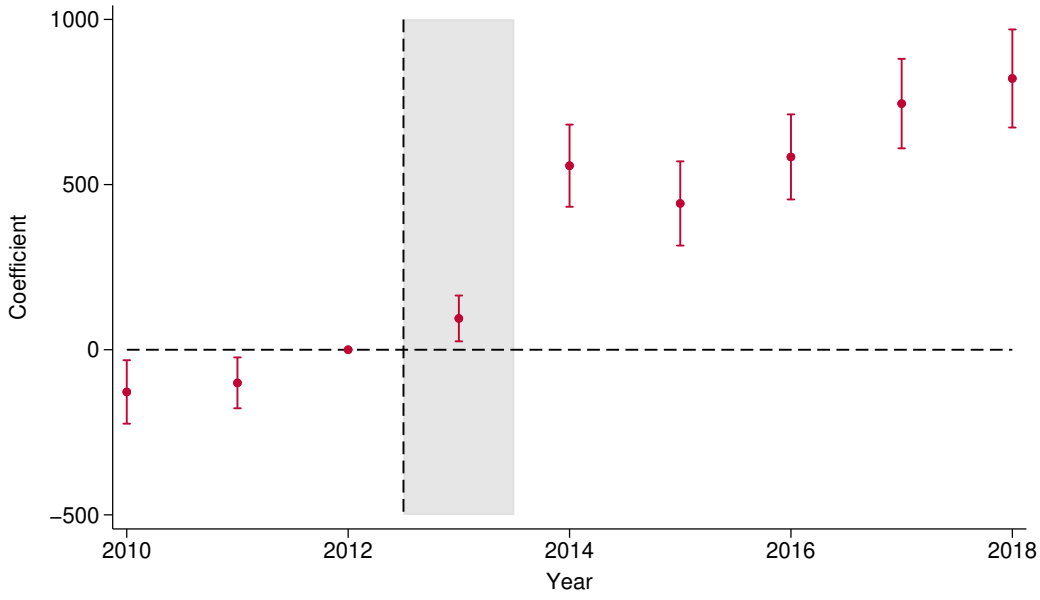
Notes: Figure shows the average fraction of total plan spending in year t on drugs approved in $t-1$. The sample is restricted to Medicare Part D Standalone Prescription Drug Plans (PDPs). Drug approval date data are from the the Food and Drug Administration's (FDA) public Drug Approval Reports by Month.

Figure 3. Effect of Technological Change on Insurer Costs

(A) Raw Data



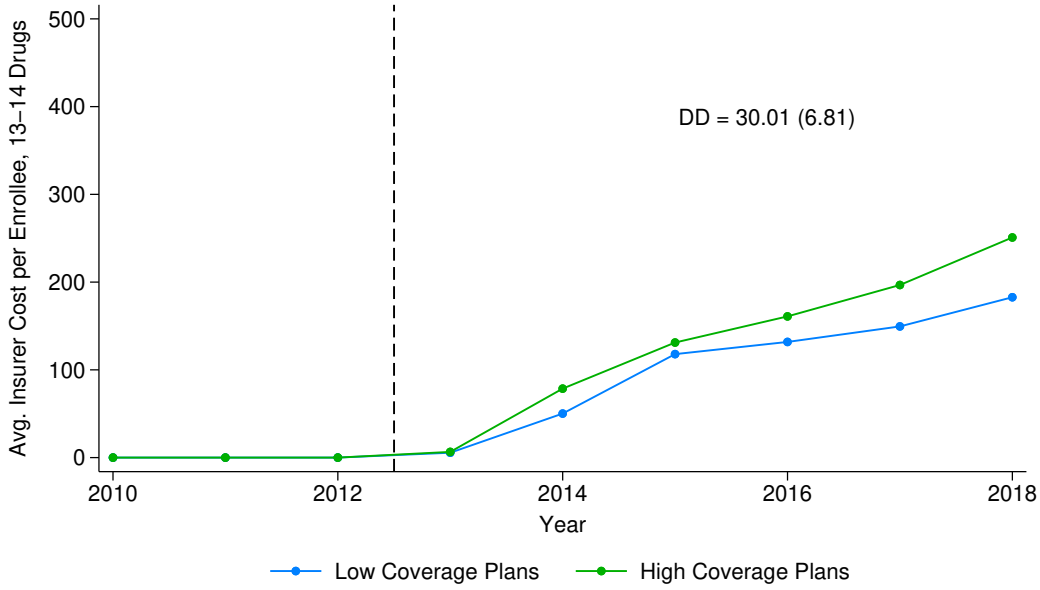
(B) Event Study



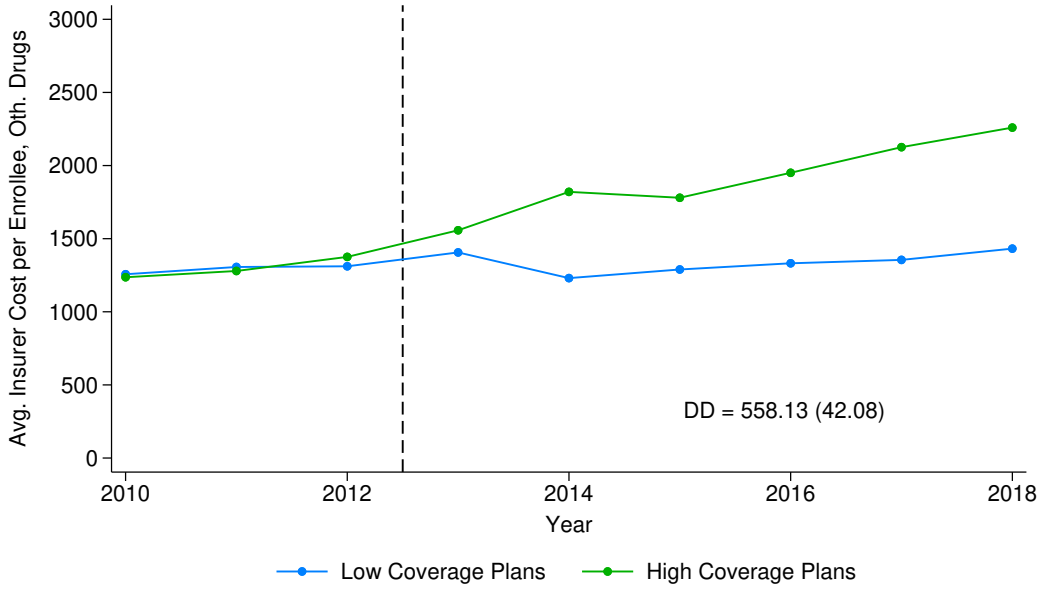
Notes: Figures show the evolution of costs for high coverage plans (green) relative to low coverage plans (blue). The full market is shown in black. High coverage plans are those offering additional coverage in the coverage gap for new drugs approved in 2013-2014. Panel A plots the raw data. Panel B shows the corresponding event study. I report the pooled difference-in-differences estimate corresponding to the event study in Equation 6 in Panel A.

Figure 4. Moral Hazard vs. Adverse Selection: Decomposing Plan Spending

(A) 2013-2014 Drugs



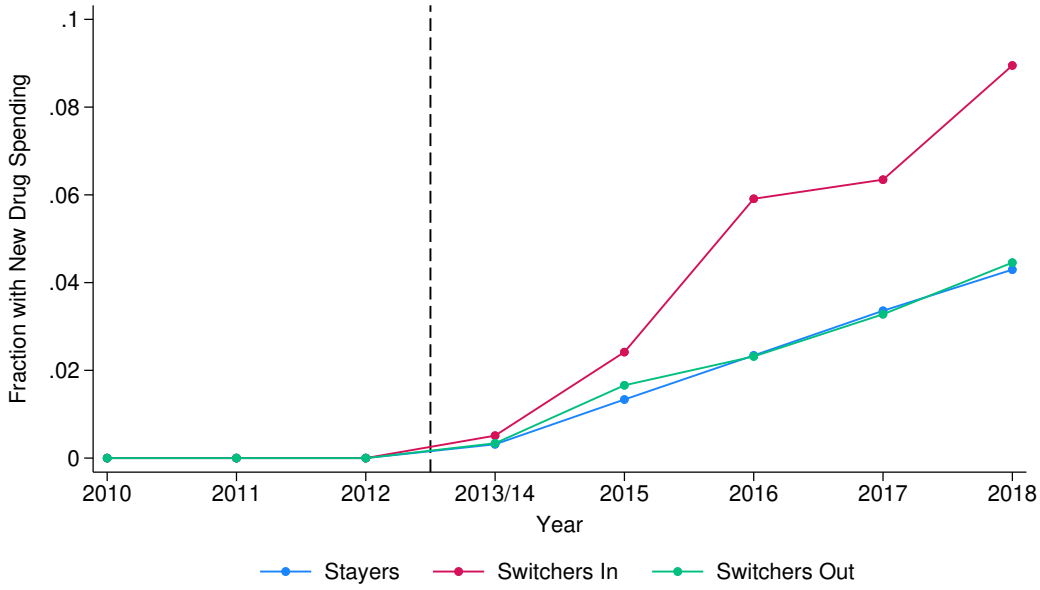
(B) All Other Drugs



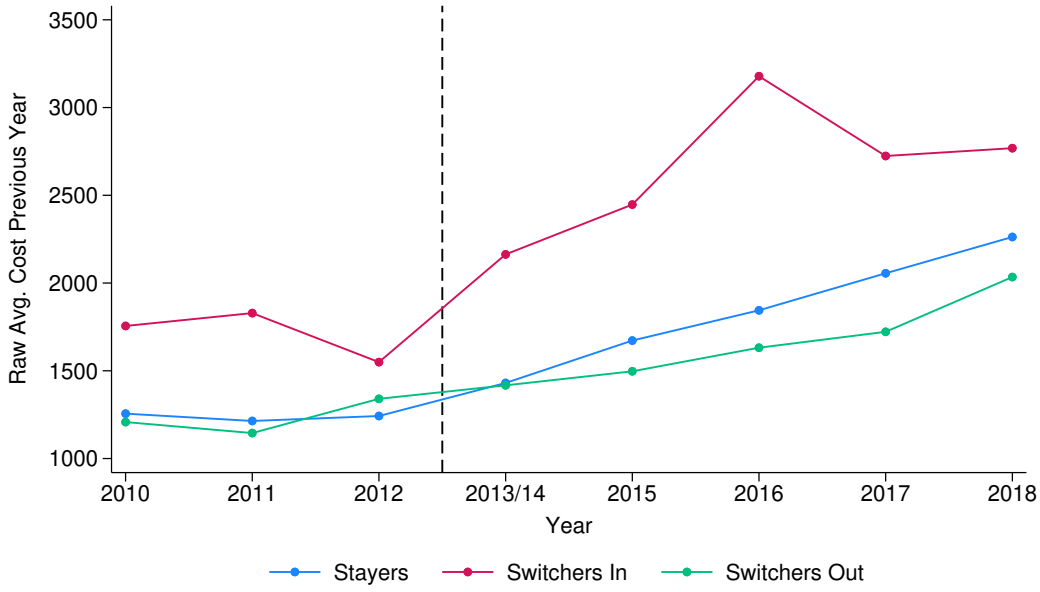
Notes: Figures show average insurer cost per enrollee for drugs in the 2013-2014 FDA cohorts (Panel A) and all other drugs (Panel B). I report the pooled difference-in-differences estimate corresponding to the event study in Equation 6 on each figure.

Figure 5. Adverse Selection Evidence: Plan Switching

(A) Pr(Using New Drugs)



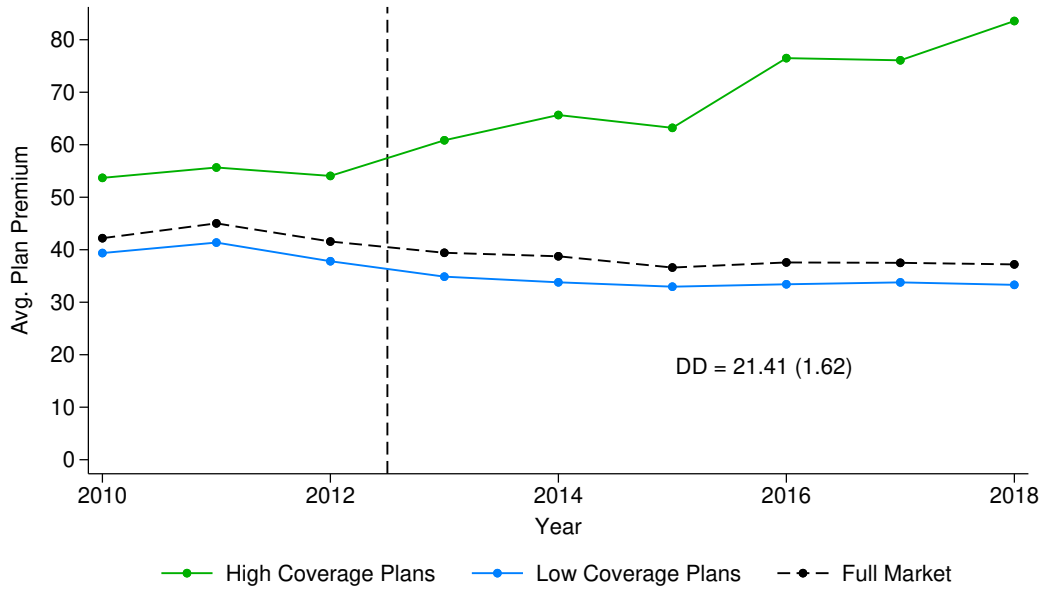
(B) Previous Year Costs



Notes: Figures shows average outcomes in the raw data for three groups: (1) individuals who switch into the high coverage plans (red), (2) individuals who switch out of the high coverage plans (green), and (3) individuals who remained enrolled in the high coverage plans. Panel A shows the probability of using the 2013-2014 drugs in a given year for each group. Panel B shows raw average previous year costs for each group. I exclude individuals who switch to a high coverage plan following the exit of their previous plan.

Figure 6. Effect of Technological Change on Monthly Premiums

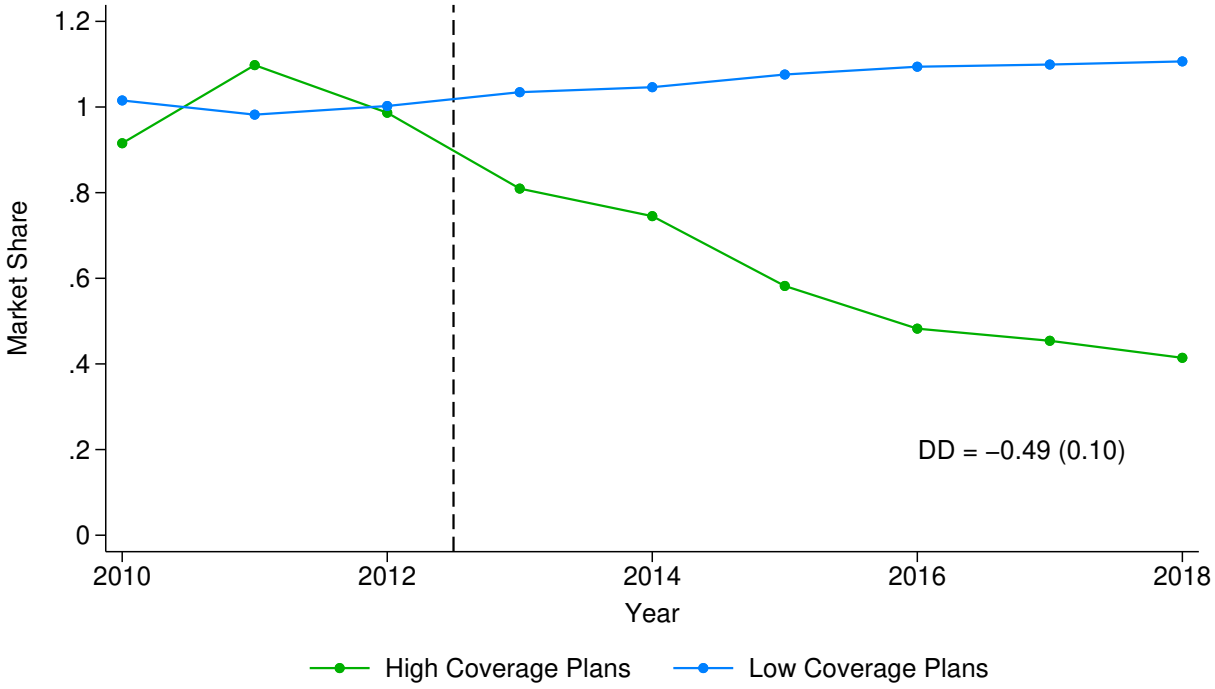
(A) Raw Data



(B) Event Study

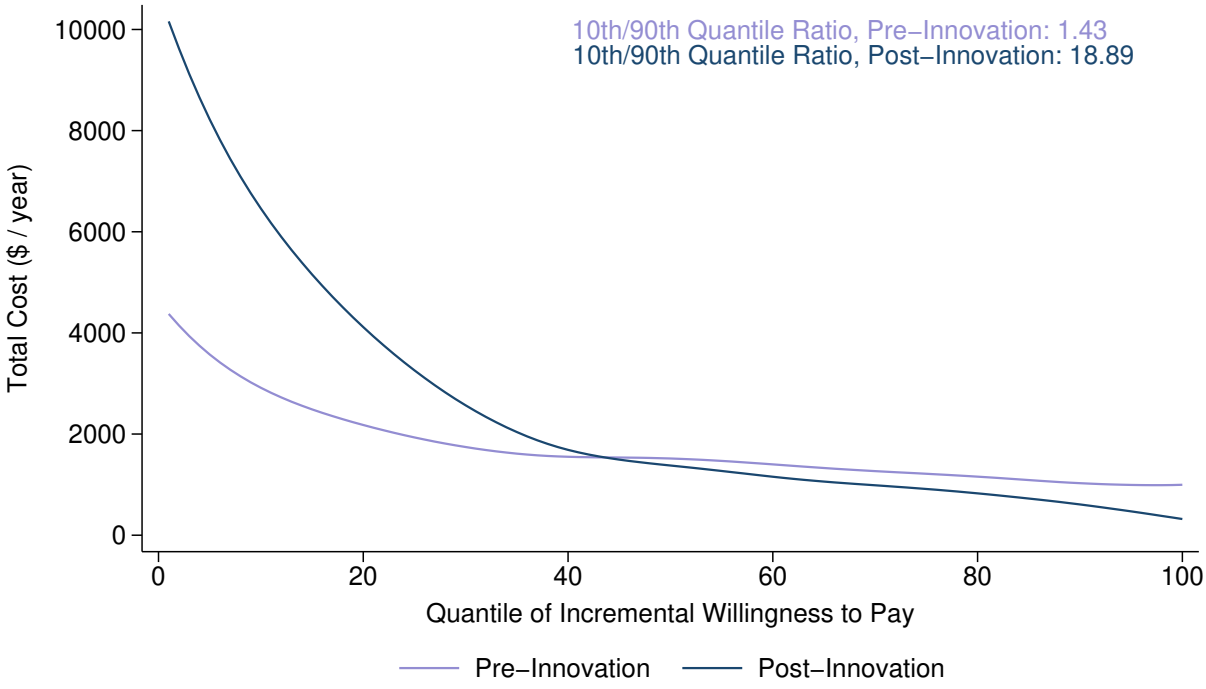
Notes: Figures show the evolution of monthly premiums for high coverage plans (green) relative to low coverage plans (blue). The full market is shown in black. High coverage plans are those offering additional coverage in the coverage gap for new drugs approved in 2013-2014. Panel A plots the raw data. Panel B shows the corresponding event study. I report the pooled difference-in-differences estimate corresponding to the event study in Equation 6 in Panel A.

Figure 7. Market Shares by Plan Type, Normalized by Pre-Period Mean



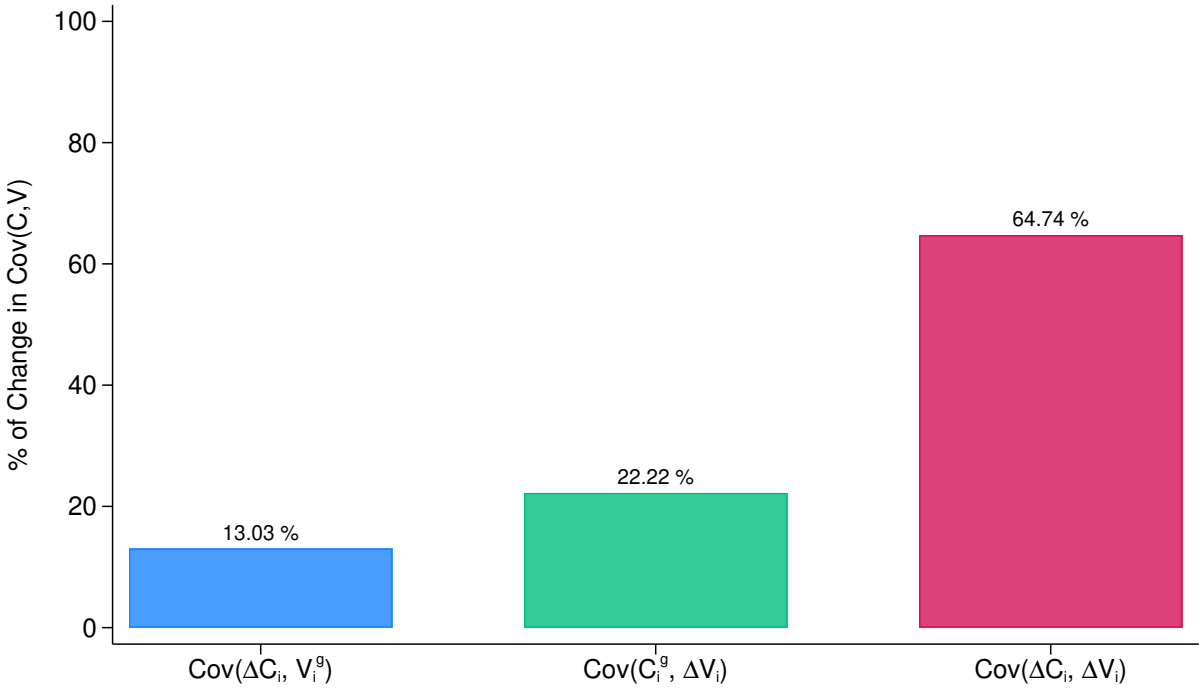
Notes: Figure shows the market share of the high coverage plans (green) and low coverage plans (blue) by year. Each series is normalized by its pre-period mean so that changes from 2013-2018 are interpretable as a proportion of the baseline mean. Difference-in-differences coefficient estimated using the pooled version of Equation 6 at the plan type-year level (i.e., excluding market fixed effects and enrollment weighting).

Figure 8. Cost and Incremental WTP for H, Pre- and Post-Innovation



Notes: Figure shows the relationship between total costs C (y-axis) and quantile q of incremental willingness to pay (x-axis), plotted using local linear regression. Individuals are arrayed on the x-axis in terms of declining incremental willingness to pay, which is constructed using Equation 9. The purple line depicts the relationship in the pre-innovation period (2010-2012) and the navy line depicts the relationship in the post-innovation period (2015-2018).

Figure 9. Selection Decomposition



Notes: Figure shows the results of the selection decomposition defined in Equation 2. To estimate the decomposition, I restrict to individuals with data both pre-innovation (2010-2012) and post-innovation (2015-2018). I estimate incremental demand for H (V_i) using estimates from the plan choice model in Equation 9, and define ΔV_i and ΔC_i as the change in average incremental demand and average costs for individual i between the pre-innovation period (2010-2012) and post-innovation period (2015-2018).

Tables

Table 1. Summary Statistics

	Full Sample	High Coverage Plans	Low Coverage Plans
	(1)	(2)	(3)
Panel A. Beneficiary Characteristics			
Age	75.53	76.65	74.89
	(7.36)	(7.36)	(7.28)
Female	0.59	0.61	0.57
	(0.49)	(0.49)	(0.49)
NH White	0.90	0.92	0.89
	(0.30)	(0.28)	(0.32)
NH Black	0.04	0.03	0.05
	(0.20)	(0.18)	(0.22)
NH Other	0.02	0.02	0.03
	(0.15)	(0.14)	(0.16)
Hispanic	0.02	0.02	0.03
	(0.16)	(0.15)	(0.16)
Num. Chronic Conditions	4.79	5.17	4.57
	(3.44)	(3.47)	(3.40)
Years Observed	6.37	7.21	5.90
	(2.48)	(2.21)	(2.49)
N (Bene-Years)	20,339,358	7,366,114	12,973,244
Panel B. Plan Characteristics			
Enrollment	489.13	283.11	500.51
	(1,852.99)	(564.89)	(1,898.19)
Avg. Plan Spend per Enrollee	1,728.24	2,684.89	1,675.39
	(2,877.43)	(4,030.69)	(2,790.49)
Average Part D Risk Score	0.95	1.06	0.95
	(0.15)	(0.06)	(0.15)
Fraction Enhanced	0.22	1.00	0.17
	(0.41)	(0.00)	(0.38)
Cover 2013-2014 Drugs	0.95	1.00	0.95
	(0.21)	(0.00)	(0.21)
Prior Auth. on 2013-2014 Drugs	1.00	1.00	1.00
	(0.00)	(0.00)	(0.00)
Years Observed	5.76	5.50	5.77
	(2.69)	(1.37)	(2.74)
N (Plan-Region-Years)	25,752	1,348	24,404

Notes: Table shows summary statistics (means and standard deviations) for the full sample (column 1) and for different types of coverage. Column (2) shows estimates for the high coverage plans. Column (3) shows estimates for low coverage plans.

Table 2. Average Patient Liability by Plan Type

	Full Sample	High Coverage Plans	Low Coverage Plans
All Drugs	205.91	136.12	275.69
	(587.00)	(258.38)	(782.78)
Top 25% Costliest	517.56	318.26	716.87
	(928.01)	(378.91)	(1,224.83)
Top 10% Costliest	1,205.05	675.76	1,734.34
	(1,360.38)	(479.50)	(1,707.38)
Observations	5,496	2,748	2,748

Notes: Table shows the average beneficiary out-of-pocket (OOP) liability per fill for different plans and different groups of drugs. Each observation is a drug-plan type combination. Column (1) shows the average beneficiary OOP across all plans, while column (2) shows the same for beneficiaries in high coverage plans and column (3) shows the same for beneficiaries in low coverage plans. The rows show different groups of drugs. The first row shows average patient OOP liabilities by plan type across all drugs. The second row shows average patient OOP liabilities by plan type for drugs where the overall average patient liability is in the top quartile. The third row shows average patient OOP liabilities by plan type for drugs where the overall average patient liability is in the top 10%. Standard deviations are shown in parentheses.

Table 3. Effect of Technological Change on Plan Costs and Premiums

	(1)	(2)	(3)
	Panel A. Average Cost		
Gap Covg. x Post	572.58***	588.01***	980.84***
	(47.57)	(45.18)	(79.43)
Baseline Mean	1700.63	1700.63	1700.63
R^2	0.12	0.19	0.25
N	21,199	21,199	21,199
	Panel B. Risk-Adjusted Average Cost		
Gap Covg. x Post	552.01***	563.00***	907.48***
	(47.77)	(45.81)	(72.39)
Baseline Mean	1701.26	1701.26	1701.26
R^2	0.10	0.16	0.20
N	20,102	20,102	20,102
	Panel C. Monthly Premium		
Gap Covg. x Post	21.25***	21.41***	35.10***
	(1.59)	(1.62)	(3.09)
Baseline Mean	41.06	41.06	41.06
R^2	0.24	0.26	0.31
N	21,199	21,199	21,199
Market FE		✓	✓
Plan Chars.			✓

Notes: Table shows difference-in-differences estimates pooling the event study coefficients β_t in Equation 6. Panel A shows the results for average costs, and Panel B shows the results for risk-adjusted average costs. Panel C shows average monthly premiums (net of rebates). Plan characteristics include an indicator for a plan being enhanced, interacted with year indicators to control for secular patterns affecting enhanced plans. All estimates include year fixed effects, are weighted by plan enrollment, and have standard errors clustered at the plan level.

Table 4. Effect of Technological Change on Plan Risk

	(1)	(2)	(3)
	Panel A. Average Part D Risk Score		
Gap Covg. x Post	0.02**	0.03**	0.11***
	(0.01)	(0.01)	(0.02)
Baseline Mean	0.97	0.97	0.97
R^2	0.06	0.12	0.34
N	19,792	19,792	19,792
	Panel B. Avg. Reinsurance Payment Per Member Per Month ($)		
Gap Covg. x Post	15.18***	15.93***	18.49***
	(3.36)	(3.13)	(2.93)
Baseline Mean	23.28	23.28	23.28
R-squared	0.22	0.24	0.30
N	19,792	19,792	19,792
Market FE		✓	✓
Plan Chars.			✓

Notes: Table shows difference-in-differences estimates pooling the event study coefficients β_t in Equation 6. Panel A shows the results for average Part D risk score and Panel B shows the results for average reinsurance payment per member per month. Plan characteristics include an indicator for a plan being enhanced, interacted with year indicators to control for secular patterns affecting enhanced plans. All estimates include year fixed effects. Regressions are weighted by total plan enrollment, and standard errors are clustered at the plan level.

Table 5. Enrollment, Prices, and Welfare in Equilibrium

	Characteristics of Equilibrium Allocation		**Comparison to Eff. Alloc. (Market Surplus)**		**Comparison to Eff. Alloc. (Ex-Ante)**	
	% in H	Rel. Price ($ / mo.)	% Eff. CS	% Eff. SS	% Eff. CS	% Eff. SS
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Pre-Post Innovation						
Pre-Innovation	22.3	50	57.4	90.1	13.7	34.2
Post-Innovation	6.4	133.33	21.8	57.4	5.0	19.4
Panel B. Counterfactuals						
Reduced Reinsurance	1.6	233.33	6.1	27.4	1.2	8.0
Perfect Risk Adjustment	35.5	25	100.0	100.0	25.8	37.8

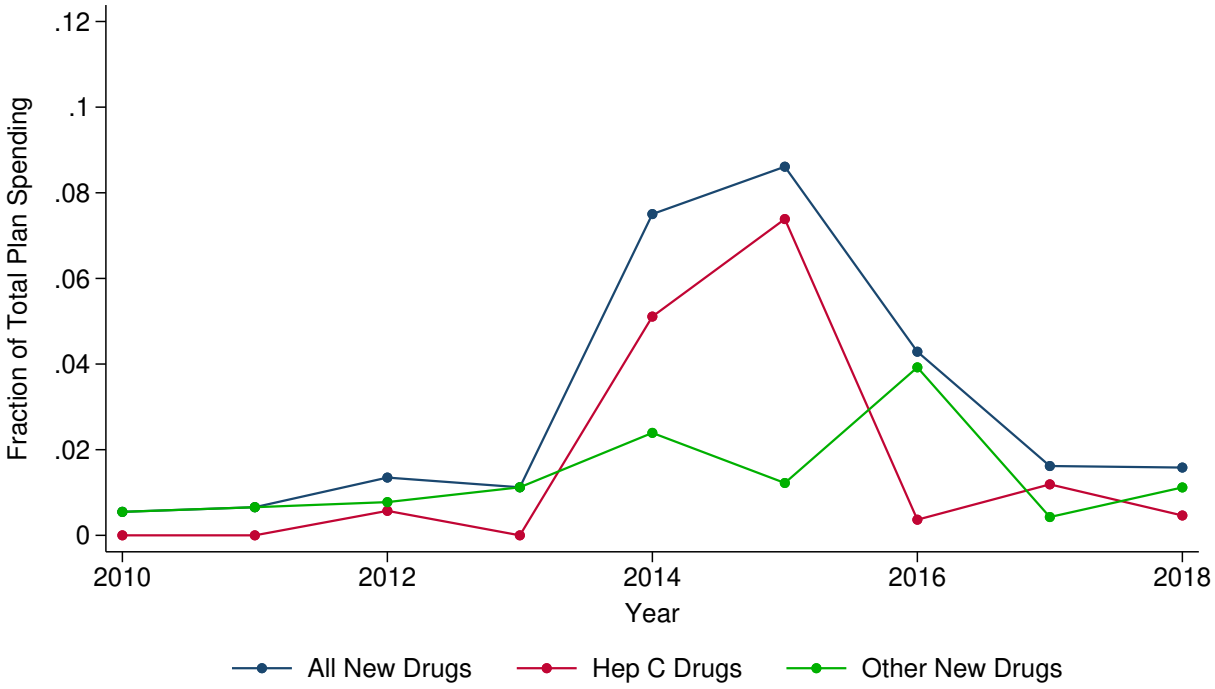
Notes: Table shows various characteristics of the equilibrium allocation. Columns (1) and (2) show the percent of the market enrolled in high coverage plans, and the relative price of those plans, in equilibrium. Columns (3) and (4) show the fraction of the efficient consumer and social surplus achieved by this equilibrium allocation using standard market surplus notions of welfare. Columns (5) and (6) show the fraction of the efficient consumer and social surplus achieved by this equilibrium allocation using the ex-ante welfare framework outlined in Hendren (2021).

Online Appendix For: Adverse Selection and Technological Change

Graeme Peterson

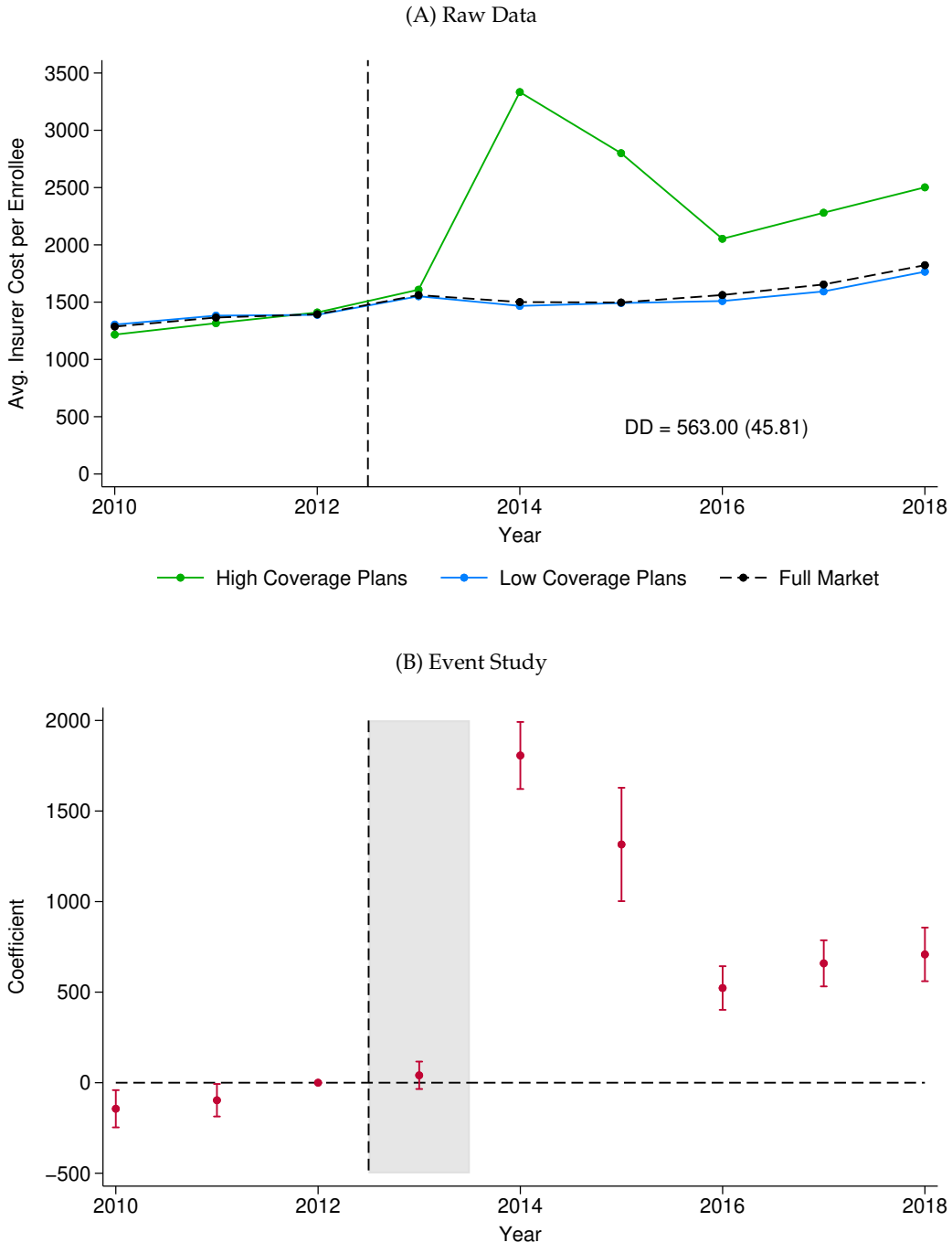
A Additional Figures and Tables

Appendix Figure A1. Fraction of Total Plan Spending on Drugs Approved Previous Year, Hepatitis C versus Other Drugs



Notes: Figure shows the average fraction of total plan spending in year t on drugs approved in $t-1$, split out by whether drugs treat Hepatitis C. The sample is restricted to Medicare Part D Standalone Prescription Drug Plans (PDPs). Drug approval date data are from the the Food and Drug Administration's (FDA) public Drug Approval Reports by Month.

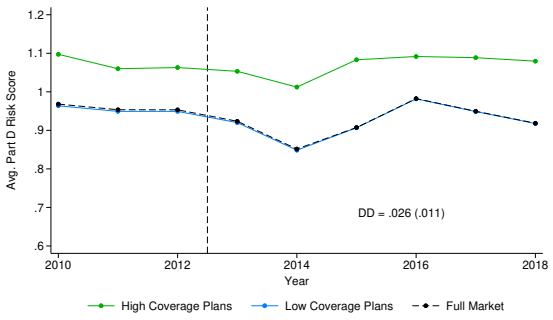
Appendix Figure A2. Effect of Technological Change on Risk-Adjusted Costs



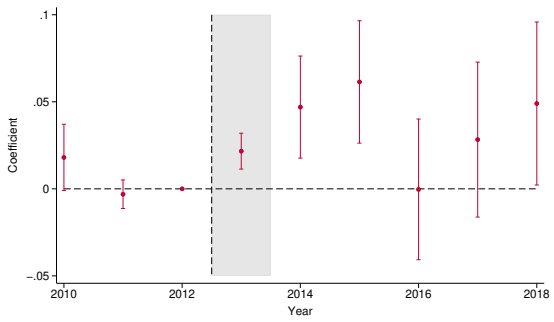
Notes: Figures show the evolution of risk-adjusted costs for high coverage plans (green) and low coverage plans (blue). High coverage plans are those offering additional coverage in the coverage gap for new drugs approved in 2013-2014. Panel A shows raw means in the data, while Panel B shows the corresponding event study.

Appendix Figure A3. Changes in Average Part D Risk Scores

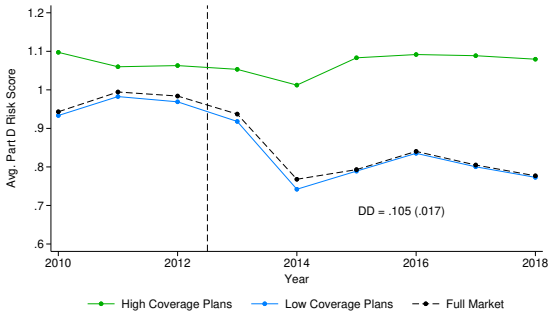
(A) Avg. Part D Risk Score, All Plans



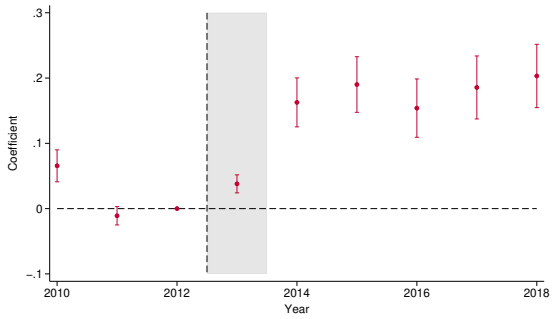
(B) Avg. Part D Risk Score, All Plans



(C) Avg. Part D Risk Score, Enhanced Only



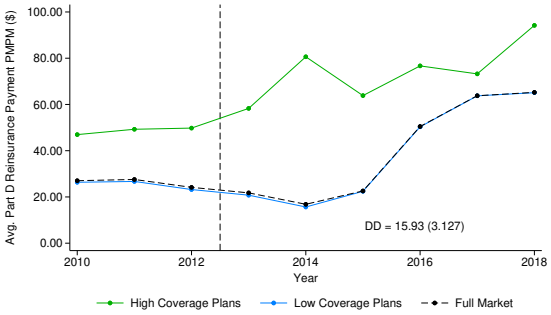
(D) Avg. Part D Risk Score, Enhanced Only



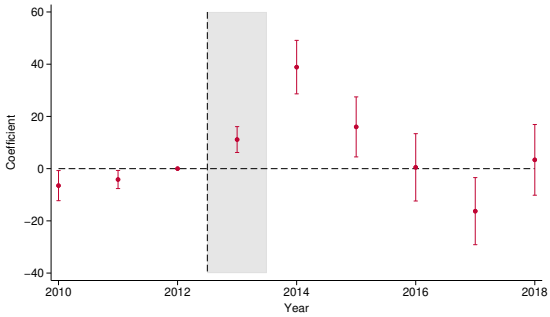
Notes: Figures plot changes in average Part D risk scores for high coverage plans (green) and low coverage plans (blue). High coverage plans are those offering additional coverage in the coverage gap for new drugs approved in 2013-2014. The left column plots the raw data, and the right column shows the corresponding event study estimated as specified in Equation 6. In Panels A and B, I use all plans in the sample. In Panel C and D, I restrict the sample to enhanced plans so that the comparison group (in blue) is comprised only of enhanced plans without gap coverage for the 2013-2014 drugs.

Appendix Figure A4. Changes in Reinsurance

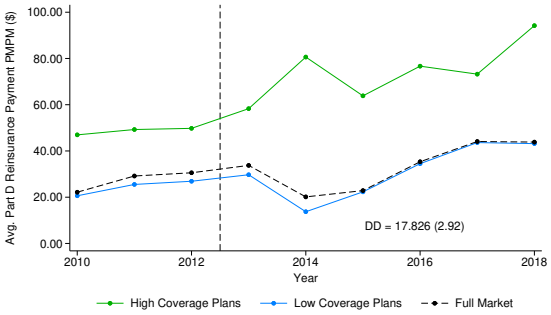
(A) Avg. Part D Reinsurance Payment Per Member Per Month, All Plans



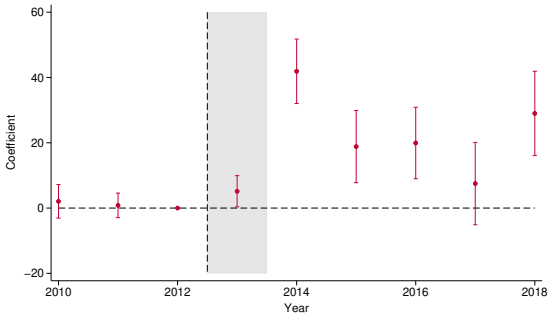
(B) Avg. Part D Reinsurance Payment Per Member Per Month, All Plans



(C) Avg. Part D Reinsurance Payment Per Member Per Month, Enhanced Only



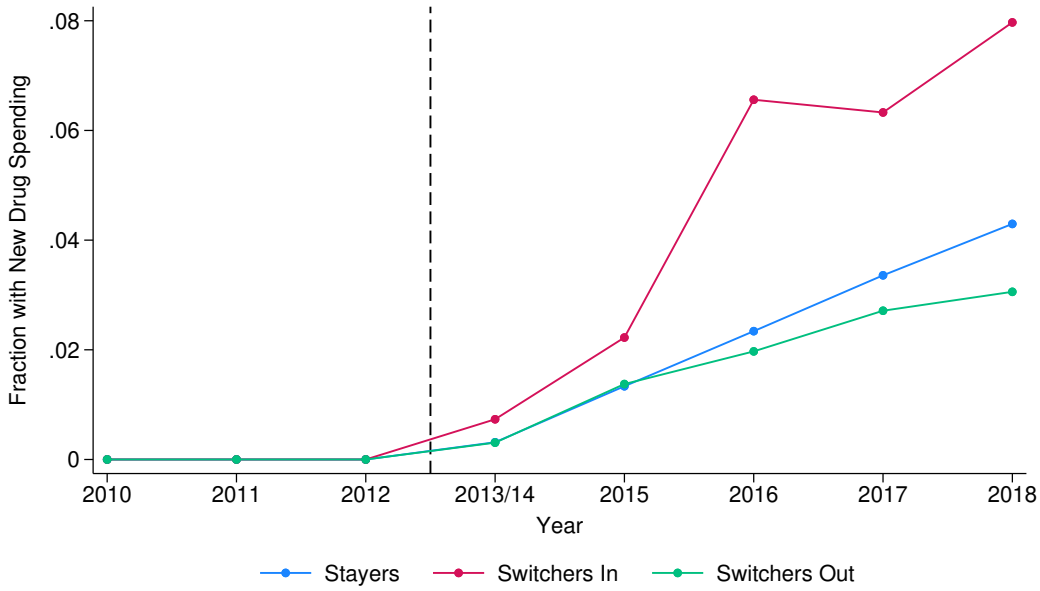
(D) Avg. Part D Reinsurance Payment Per Member Per Month ($), Enhanced Only



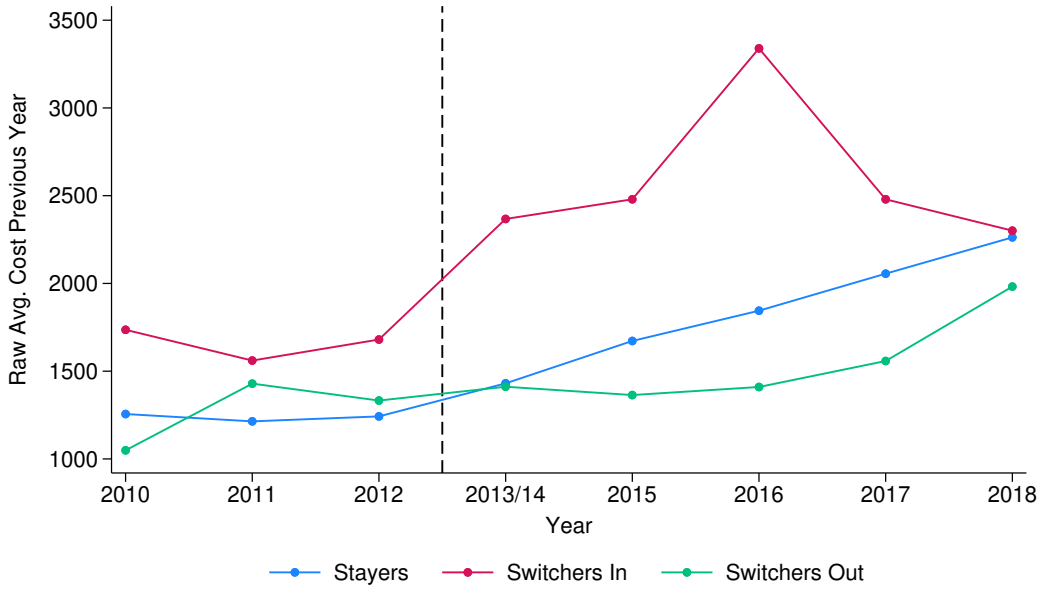
Notes: Figures plot changes in plans' average reinsurance payment per member per month for high coverage plans (green) and low coverage plans (blue). High coverage plans are those offering additional coverage in the coverage gap for new drugs approved in 2013-2014. The left column plots the raw data, and the right column shows the corresponding event study estimated as specified in Equation 6. In Panels C and D, I restrict the sample to enhanced plans so that the comparison group (in blue) is comprised only of enhanced plans without gap coverage for the 2013-2014 drugs.

Appendix Figure A5. Switching to and from Enhanced Plans Only

(A) Pr(Using New Drugs)

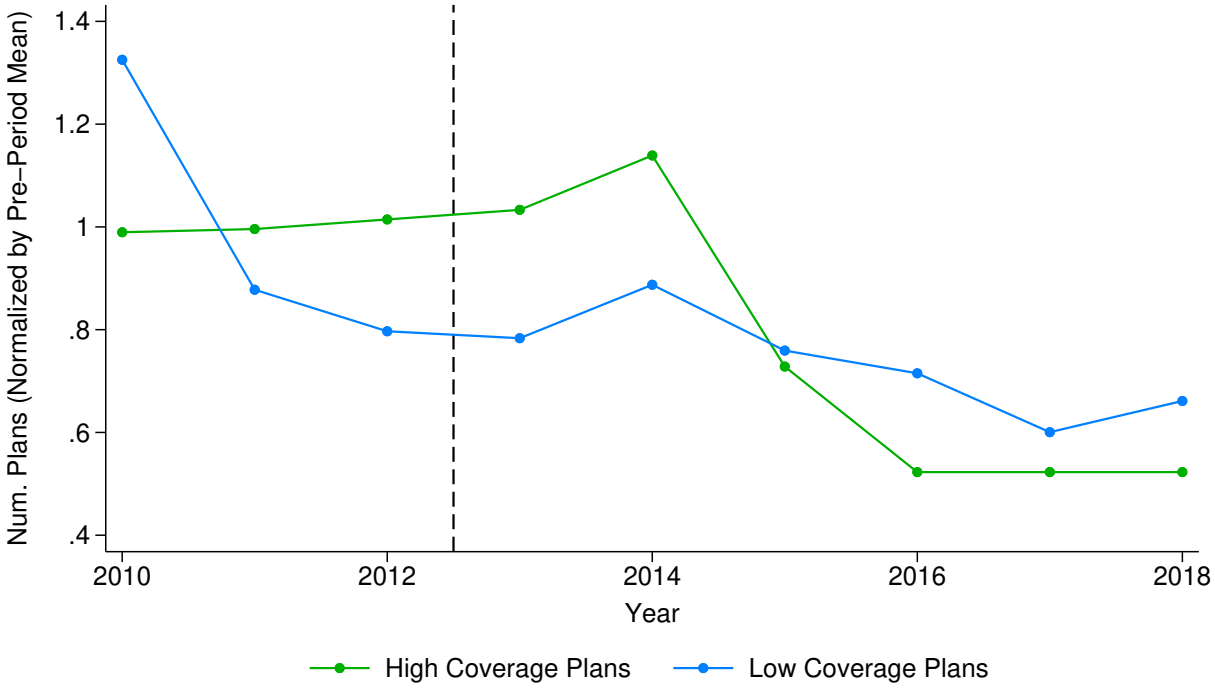


(B) Previous Year Costs



Notes: Figures shows outcomes for three groups: (1) individuals who switch into the high coverage plans (red), (2) individuals who switch out of the high coverage plans (green), and (3) individuals who remained enrolled in the high coverage plans (blue). High coverage plans are those offering additional coverage in the coverage gap for new drugs approved in 2013-2014. Panel A shows the probability of using new drugs in a given year for each group. Panel B shows raw average previous year costs for each group. I exclude individuals who switch to a high coverage plan following the exit of their previous plan, and I restrict to individuals who switch between enhanced plans.

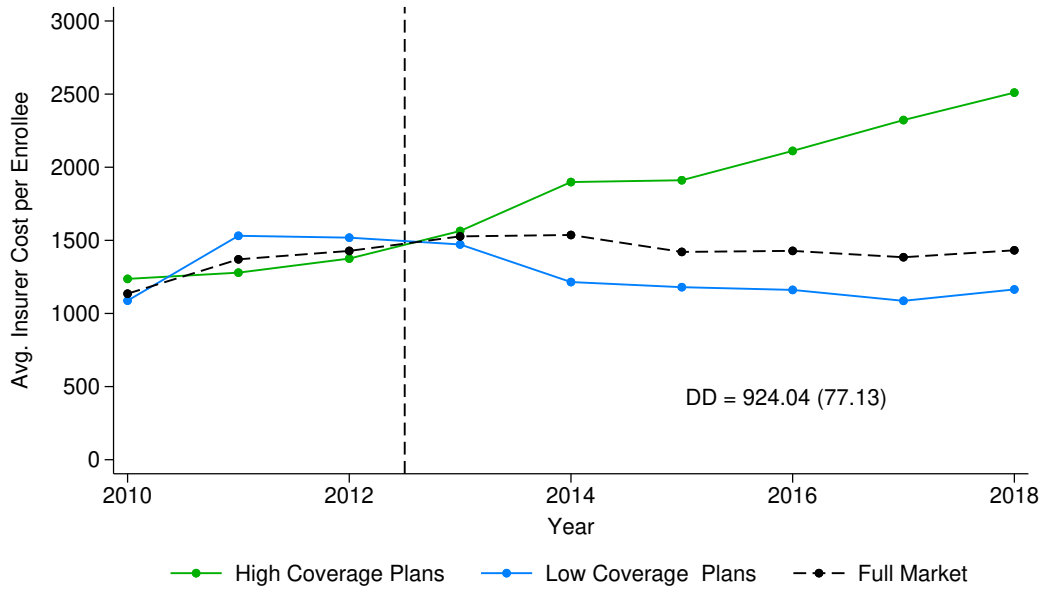
Appendix Figure A6. Number of Plans by Type, Normalized by Pre-Period Mean



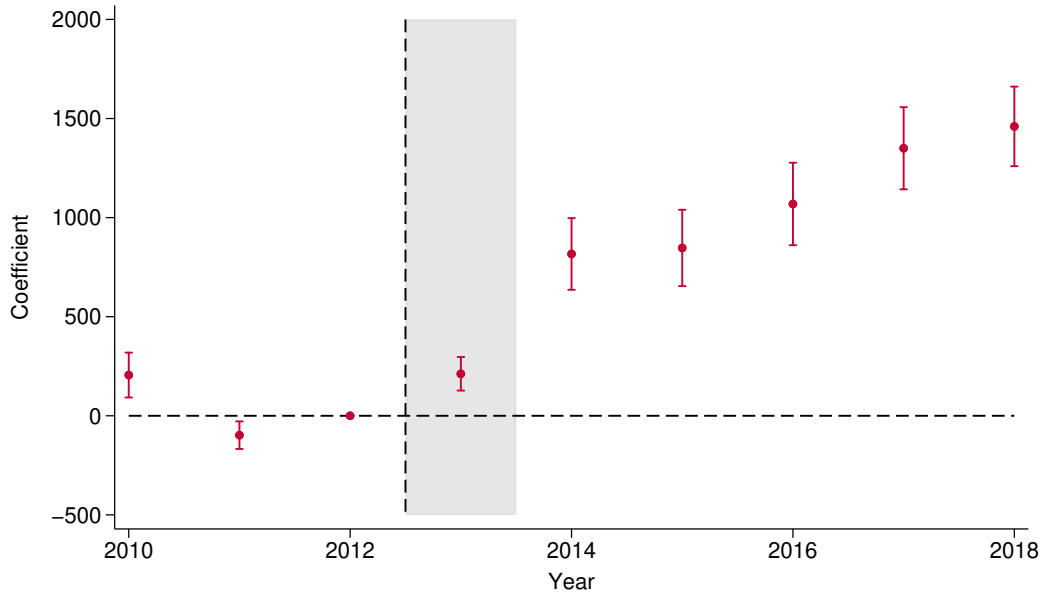
Notes: Figure shows the number of plans by type, with high coverage plans shown in green and low coverage plans shown in blue. Each series in normalized by its pre-period (2010-2012) mean so that changes from 2013-2018 are interpretable in percentage terms. The large decline in low coverage plans from 2010 to 2011 is likely the result of a CMS policy that required "meaningful differences" across plans and led to a large number of plans being removed from the market.

Appendix Figure A7. Effect of Technological Change on Insurer Costs, Enhanced Plans Only

(A) Raw Data

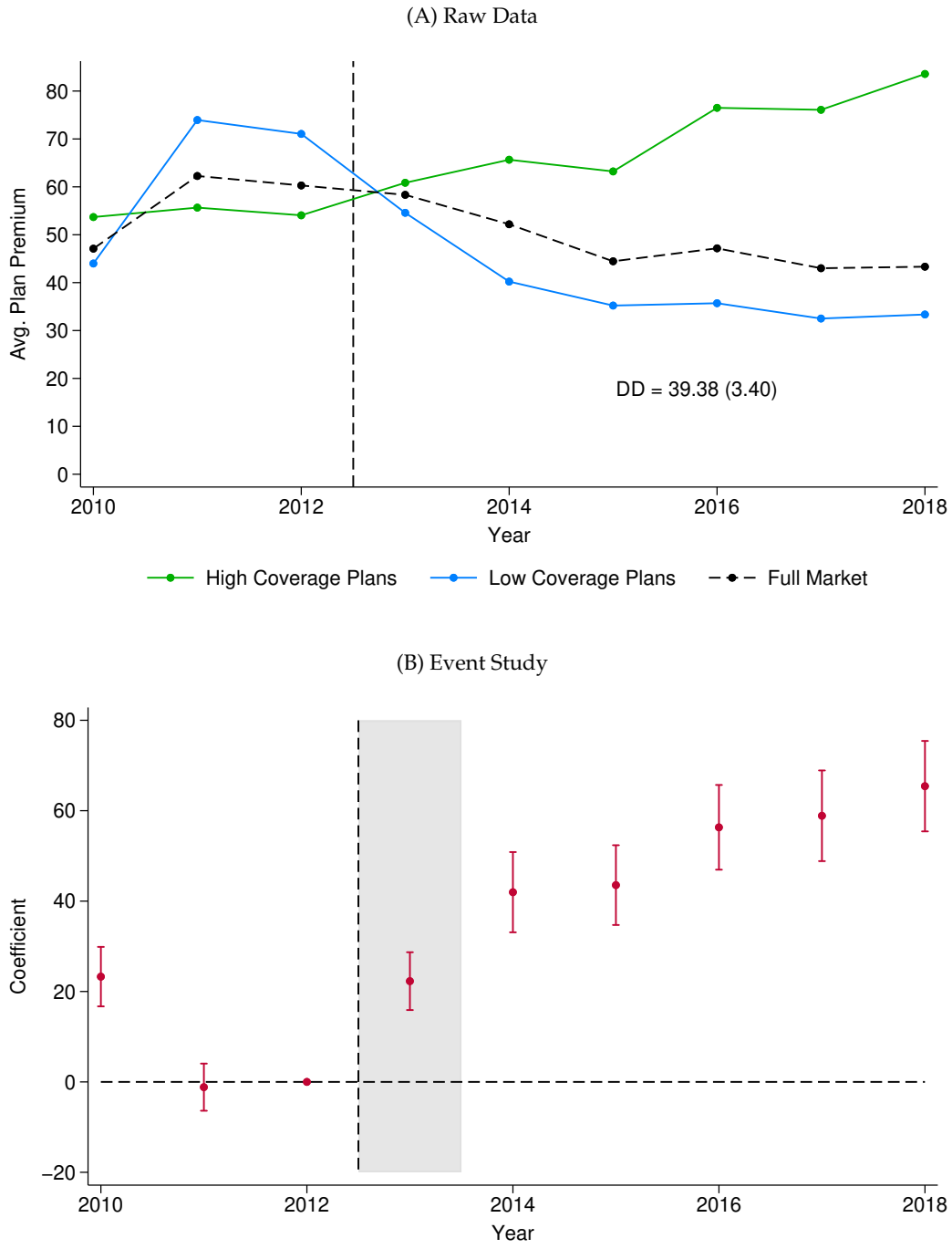


(B) Event Study



Notes: Figures show the evolution of costs for high coverage plans (green) relative to low coverage plans (blue), restricting only to enhanced plans. High coverage plans are those offering additional coverage in the coverage gap for new drugs approved in 2013-2014. Panel A plots the raw means by year and plan type. Panel B plots the β_t coefficients from Equation 6.

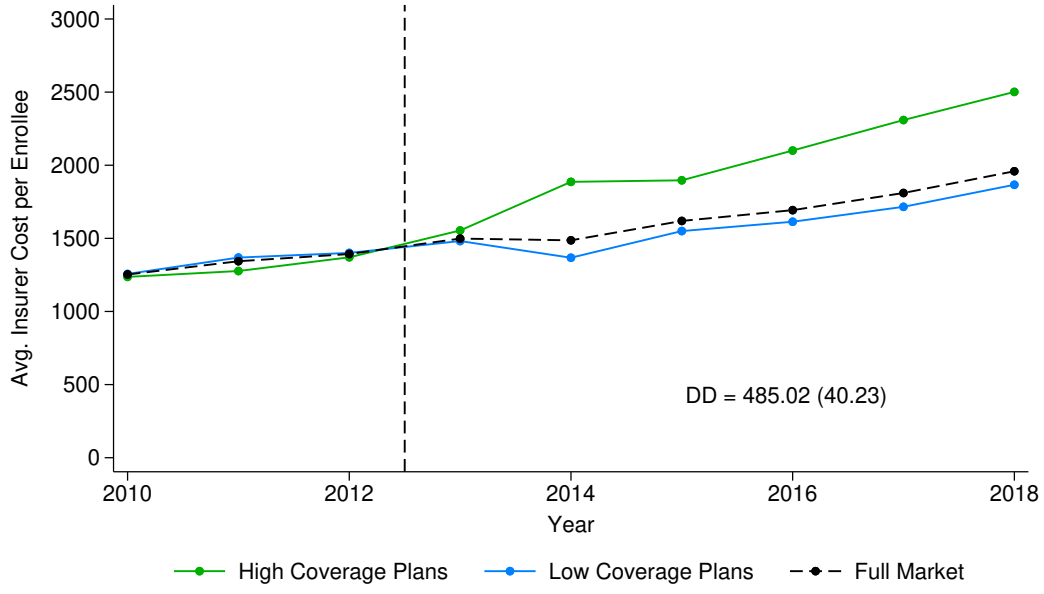
Appendix Figure A8. Effect of Technological Change on Insurance Premiums, Enhanced Plans Only



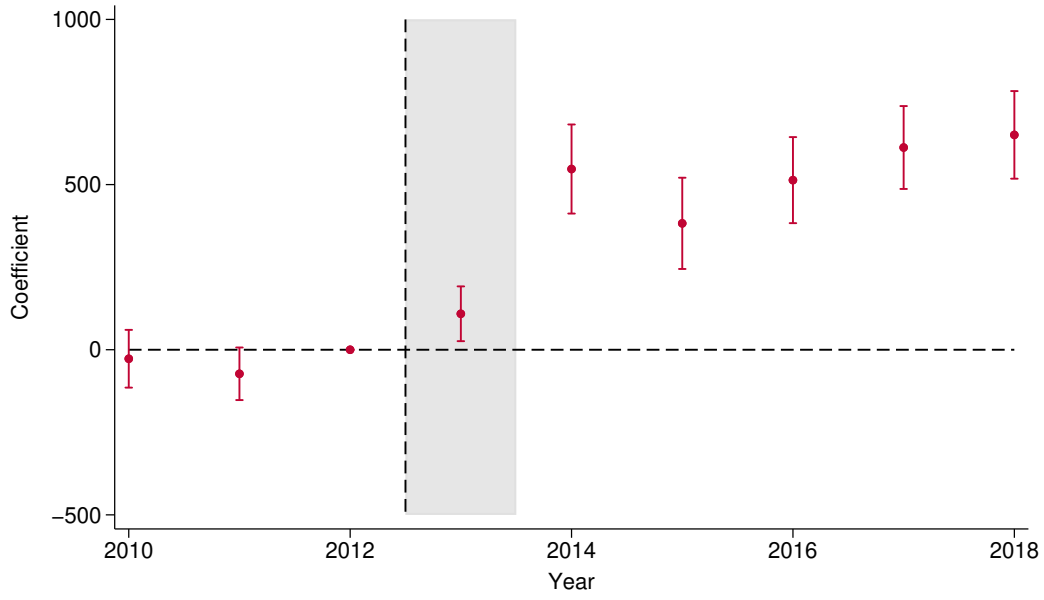
Notes: Figures show the evolution of premiums for high coverage plans (green) relative to low coverage plans (blue), restricting only to enhanced plans. High coverage plans are those offering additional coverage in the coverage gap for new drugs approved in 2013-2014. Panel A plots the raw means by year and plan type. Panel B plots the β_t coefficients from Equation 6.

Appendix Figure A9. Effect of Technological Change on Insurer Costs, Operating in 2010

(A) Raw Data



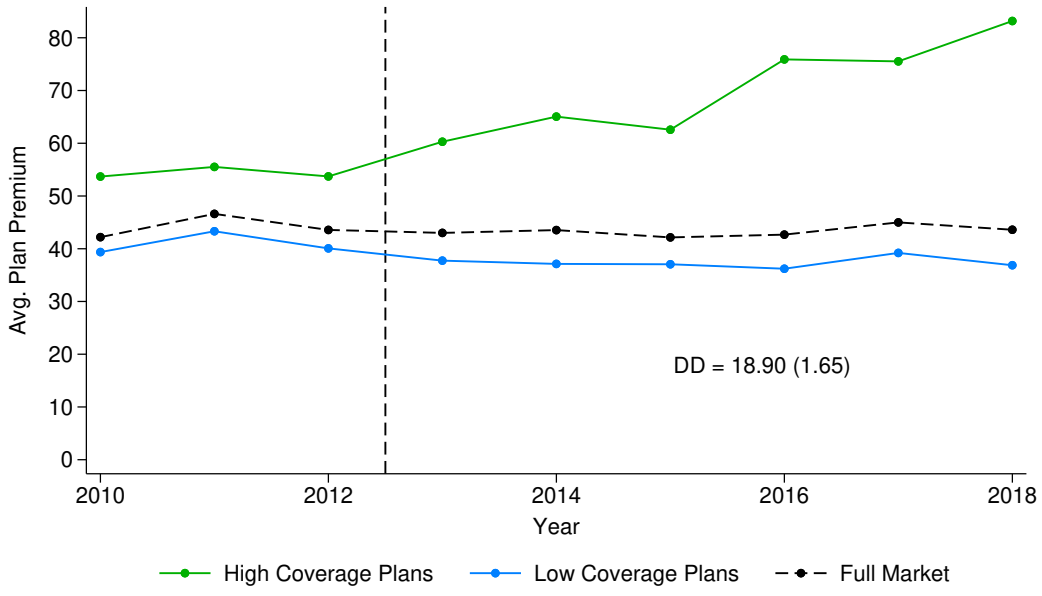
(B) Event Study



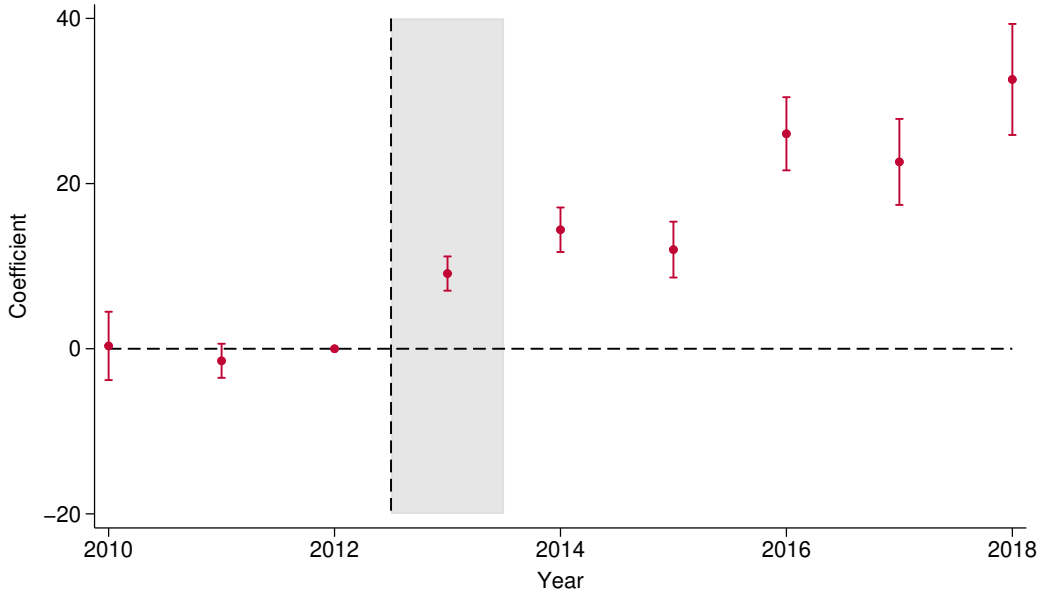
Notes: Figures show the evolution of costs for high coverage plans (green) relative to low coverage plans (blue), restricting only to plans in operation in 2010. High coverage plans are those offering additional coverage in the coverage gap for new drugs approved in 2013-2014. Panel A plots the raw means by year and plan type. Panel B plots the β_t coefficients from Equation 6.

Appendix Figure A10. Effect of Technological Change on Monthly Premiums, Operating in 2010

(A) Raw Data

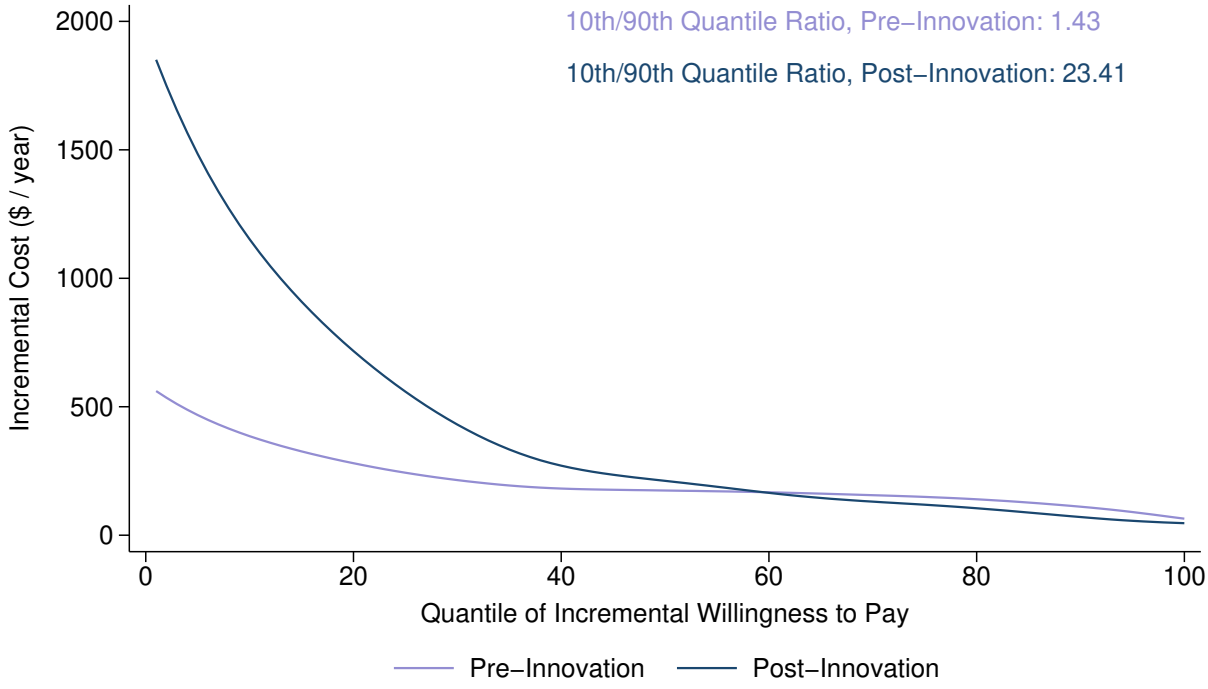


(B) Event Study



Notes: Figures show the evolution of premiums for high coverage plans (green) relative to low coverage plans (blue), restricting only to plans in operation in 2010. High coverage plans are those offering additional coverage in the coverage gap for new drugs approved in 2013-2014. Panel A plots the raw means by year and plan type. Panel B plots the β_t coefficients from Equation 6.

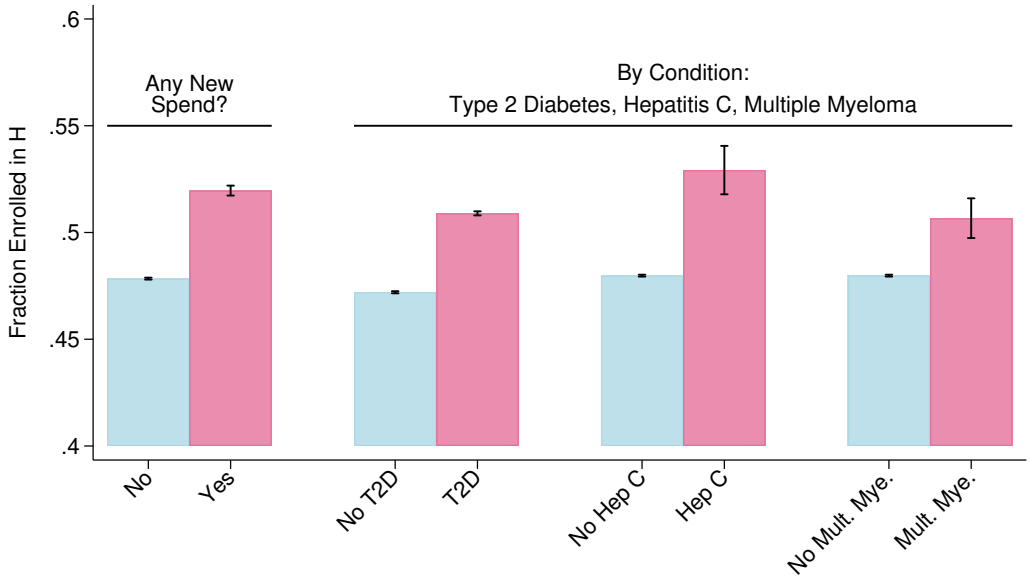
Appendix Figure A11. Incremental Cost and Incremental WTP for H, Pre- and Post-Innovation



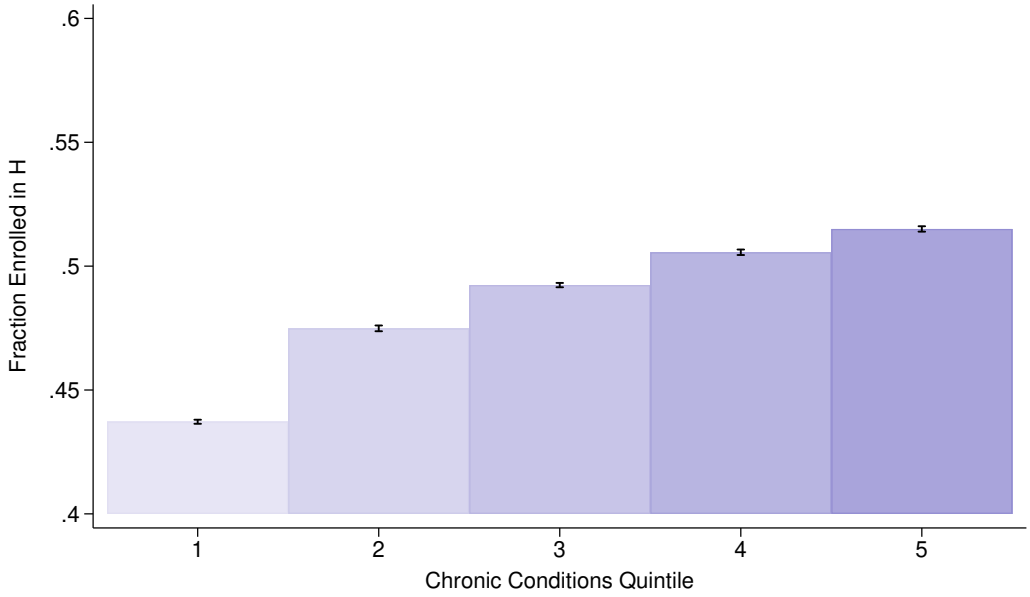
Notes: Figure shows the relationship between incremental costs ΔC (y-axis) and quantile q of incremental willingness to pay (x-axis), plotted using local linear regression. Individuals are arrayed on the x-axis in terms of declining incremental willingness to pay, which is constructed using Equation 9. The purple line depicts the relationship in the pre-innovation period (2010-2012) and the navy line depicts the relationship in the post-innovation period (2015-2018).

Appendix Figure A12. Pre-Innovation Sorting by Sickness and Future Utilization

(A) By Future New Drug Use and Health Conditions

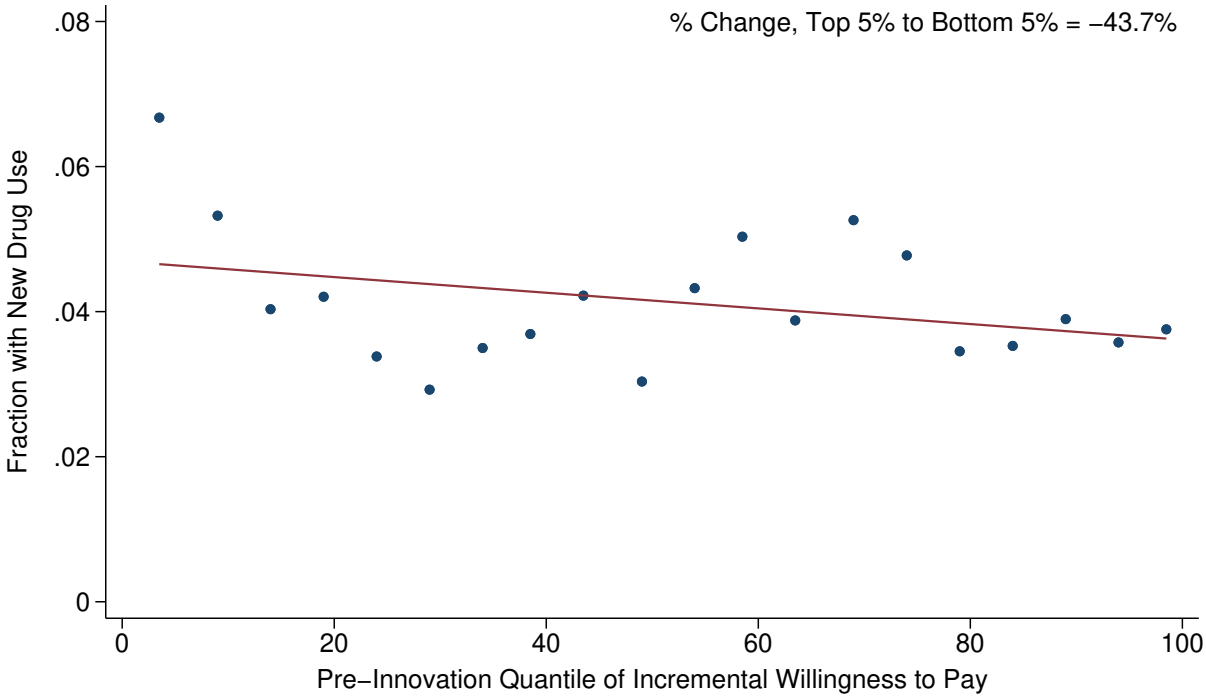


(B) By Chronic Conditions Quintile



Notes: Figures show the fraction of individuals enrolled in a high coverage plan (H) by group during the pre-innovation period (2010-2012). Panel A shows this fraction split out by individuals' future use of new drugs and by three different conditions for which there were new innovations in 2013-2014: Type 2 diabetes, Hepatitis C, and multiple myeloma. Panel B shows this fraction split out by chronic conditions quintile.

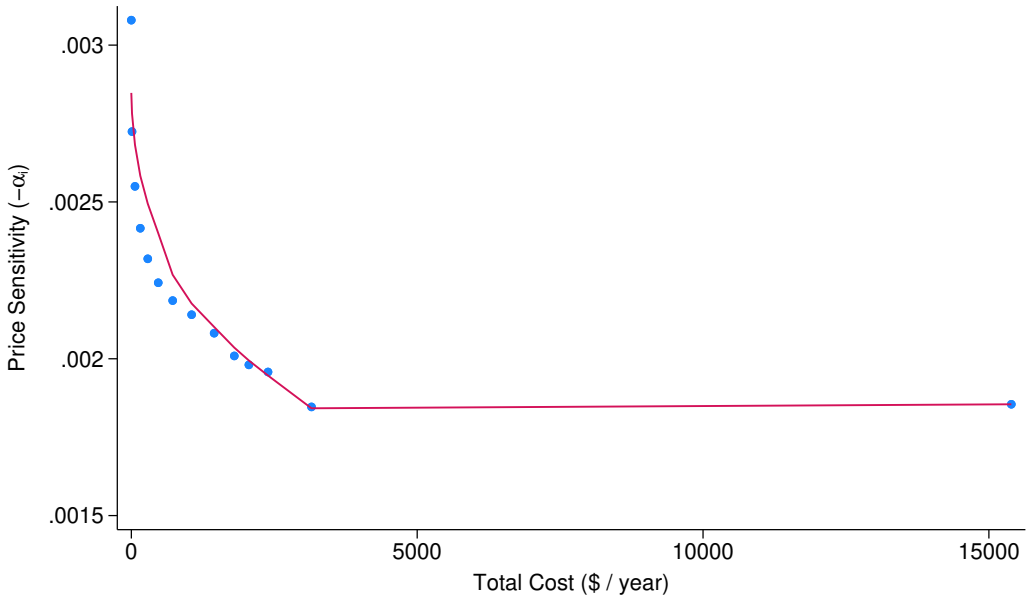
Appendix Figure A13. Fraction with New Drug Spending by Pre-Innovation Incremental WTP for H



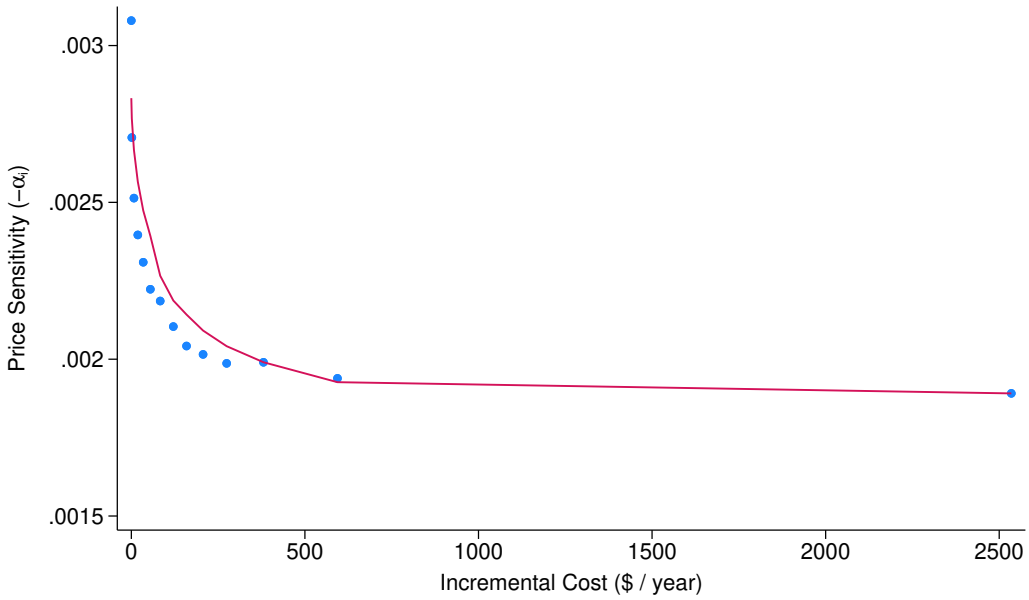
Notes: Figure shows the fraction of individuals who have any new drug spending stratified by their pre-innovation (2010-2012) incremental willingness to pay for additional risk protection in the high coverage plans. Incremental willingness to pay quantiles are ordered so that the 1st quantile corresponds to the highest incremental willingness to pay.

Appendix Figure A14. Relationship between Price Sensitivity and Cost

(A) Total Cost ($ / year)



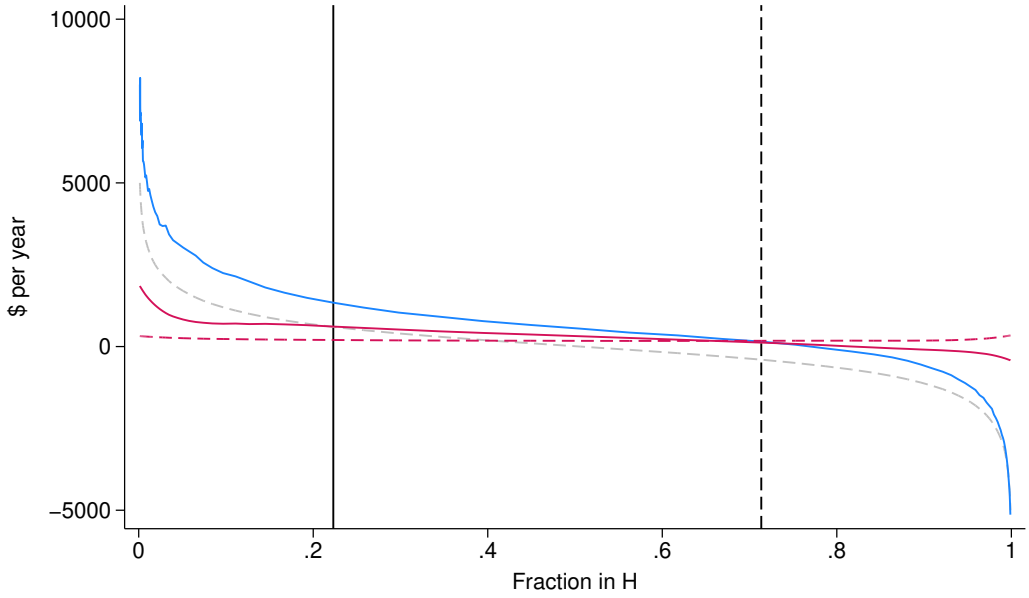
(B) Incremental Cost ($ / year)



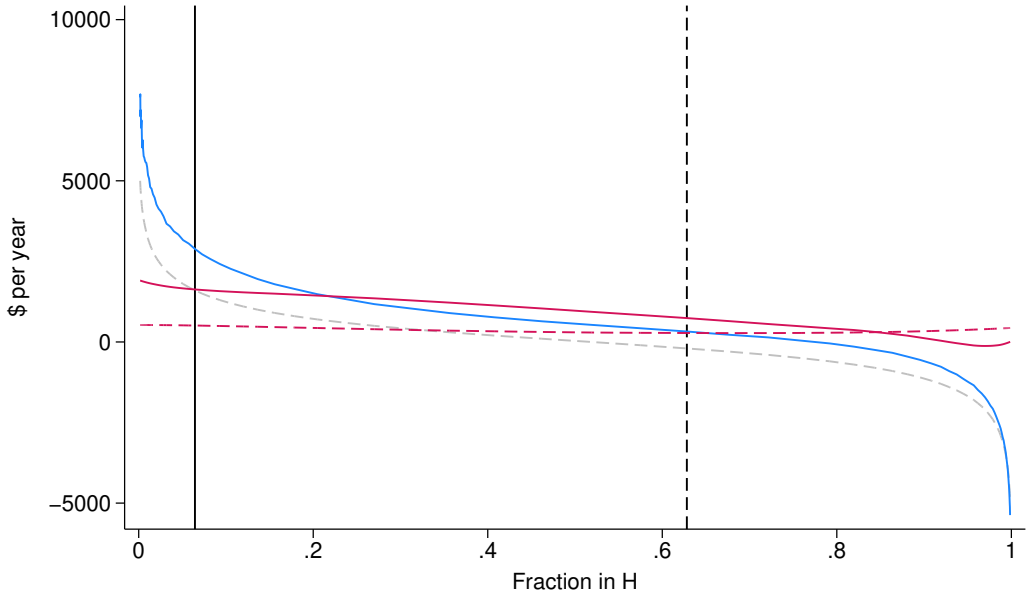
Notes: Figures show estimated price coefficients $\hat{\alpha}(x_{i,t})$ from Equation 7 plotted against total cost (Panel A) and incremental cost (Panel B). The figures show a downward sloping relationship between price sensitivity and cost, consistent with adverse selection.

Appendix Figure A15. Demand and Cost Curves

(A) Pre-Innovation (2010-2012)



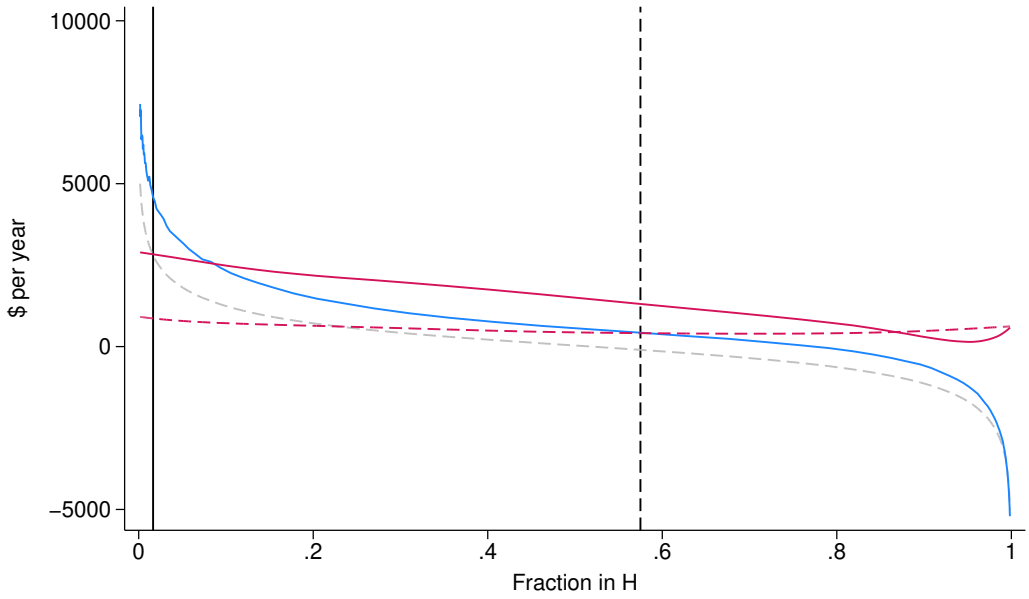
(B) Post-Innovation (2015-2018)



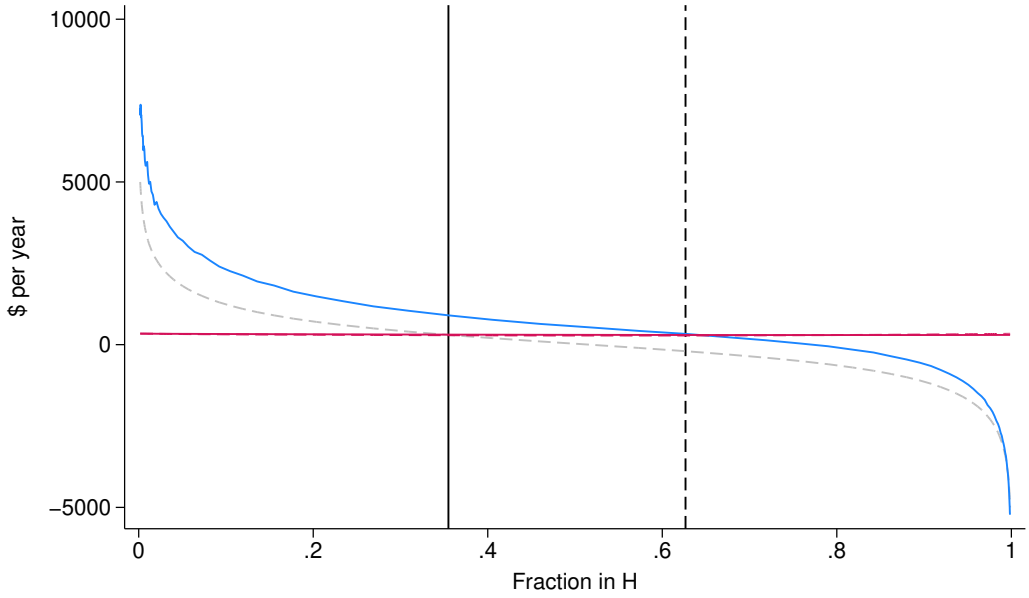
Notes: Figures show ex-ante demand $W(s)$ (blue), market demand $D(s)$ (dashed gray), incremental average cost $\Delta AC(s)$ (solid red), and incremental marginal cost $\Delta MC(s)$ (dashed red) curves in the pre-innovation period (Panel A) and post-innovation period (Panel B). The solid vertical black line shows the equilibrium allocation s^*_{eqm} determined by the intersection of market demand and average cost. The dashed vertical black line shows the ex-ante efficient allocation s^*_{eff} determined by the intersection of ex-ante demand and marginal cost.

Appendix Figure A16. Demand and Cost Curves, Counterfactuals

(A) Reduced Reinsurance



(B) Perfect Risk Adjustment



Notes: Figures show ex-ante demand $W(s)$ (blue), market demand $D(s)$ (dashed gray), incremental average cost $\Delta AC(s)$ (solid red), and incremental marginal cost $\Delta MC(s)$ (dashed red) curves. Panel A shows these curves for a counterfactual with reduced reinsurance, while Panel B shows them for a counterfactual with perfect risk adjustment. The solid vertical black line shows the equilibrium allocation s^*_{eqm} determined by the intersection of market demand and average cost. The dashed vertical black line shows the ex-ante efficient allocation s^*_{eff} determined by the intersection of ex-ante demand and marginal cost.

Appendix Table A1. Robustness: Specification Checks

	Issuer FEs		Plan Char. x Year Controls		Plan Generosity x Year Controls		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A. Raw Average Cost						
Gap Covg. x Post	587.40***	561.68***	585.56***	695.01***	980.15***	255.92***	938.84***
	(44.42)	(40.50)	(44.75)	(53.51)	(79.41)	(53.90)	(72.27)
Baseline Mean	1700.63	1700.63	1700.63	1700.63	1700.63	1700.63	1700.63
R^2	0.59	0.60	0.35	0.23	0.25	0.25	0.27
	Panel B. Monthly Premium						
Gap Covg. x Post	16.00***	16.09***	23.09***	24.55***	35.09***	5.70*	31.28***
	(1.42)	(1.48)	(1.52)	(2.10)	(3.09)	(3.15)	(2.46)
Baseline Mean	41.06	41.06	41.06	41.06	41.06	41.06	41.06
R^2	0.65	0.65	0.37	0.31	0.31	0.44	0.27
N	21,194	21,194	21,199	21,199	21,199	21,199	21,199
Issuer FE (Contract)	✓						
Issuer FE (Mktg. Org.)		✓					
Natl. PDP x Year			✓				
Below Bench. x Year				✓			
Reduced C-S x Year					✓		
Low Ded. x Year						✓	
Low Pre-ICL C-S x Year							✓

Notes: Table shows difference-in-differences estimates pooling the event study coefficients β_t in Equation 6. Columns (1) and (2) show estimates with issuer fixed effects, first by contract ID and then by organization marketing name. Columns (3) and (4) show difference-in-differences estimates controlling for differential trends for national PDPs and PDPs whose premiums are below the benchmark, respectively. Columns (5)-(7) show difference-in-differences estimates controlling for differential trends among plans with generosity in other phases of the Part D: reduced cost-sharing, lower deductibles, and lower cost-sharing specifically in the initial coverage phase. All regressions are weighted by plan enrollment, with standard errors clustered at the plan level.

Appendix Table A2. Robustness: Sample Checks

	Enhanced Only		Operating in 2010	
	(1)	(2)	(3)	(4)
	Panel A. Raw Average Cost			
Gap Covg. x Post	917.68***	924.04***	472.65***	485.02***
	(73.38)	(77.13)	(41.28)	(40.23)
Baseline Mean	1670.66	1670.66	1700.48	1700.48
R^2	0.25	0.30	0.20	0.29
N	3,720	3,720	13,034	13,034
	Panel B. Monthly Premium			
Gap Covg. x Post	39.40***	39.38***	18.72***	18.90***
	(3.06)	(3.40)	(1.55)	(1.65)
Baseline Mean	65.74	65.74	41.78	41.78
R^2	0.22	0.27	0.21	0.24
N	3,720	3,720	13,034	13,034
Year FE	✓	✓	✓	✓
Market FE		✓		✓

Notes: Table shows difference-in-differences estimates pooling the event study coefficients β_t in Equation 6. Columns (1) and (2) show estimates for a sample of enhanced plans only. Columns (3) and (4) show estimates for plans operating in 2010. All regressions are weighted by plan enrollment, with standard errors clustered at the plan level.

B Theory Appendix

B.1 General Formula for the Value of Insurance

I begin by reproducing the formula for the value of insurance from Cutler and Zeckhauser (2000) without the assumption that insurance is priced at individual-specific cost. This nests the case in their handbook chapter (where $p = \pi m$) and will be useful for characterizing changes in the value of insurance under adverse selection (where prices are not actuarially fair).

Start from the second-order Taylor approximation of the value of uninsurance (p. 573, footnote 8):

$$\begin{aligned}
V_U &= (1-\pi)\left[u(y-p) - u'p + \frac{1}{2}u''p^2\right] + \pi\left[u(y-p) + u'(m-p) + \frac{1}{2}u''(m-p)^2\right] \\
&= u(y-p) + u'\left[(1-\pi)p - \pi(m-p)\right] + \frac{1}{2}u''\left[(1-\pi)p^2 + \pi(m-p)^2\right] \\
&= u(y-p) + u'\left[p - p\pi - m\pi + p\pi)\right] + \frac{1}{2}u''\left[p^2 - p^2\pi + m^2\pi - 2pm\pi + p^2\pi\right] \\
&= u(y-p) - u'\left[p - m\pi\right] + \frac{1}{2}u''\left[p^2 + m^2\pi - 2pm\pi\right]
\end{aligned}$$

Then the value of insurance is $V_I = u(y-p)$ minus V_U:

$$\begin{aligned}
V_I - V_U &= u(y-p) - \left(u(y-p) - u'\left[p - m\pi\right] + \frac{1}{2}u''\left[p^2 + m^2\pi - 2pm\pi\right]\right) \\
&= -u'\left[p - m\pi\right] - \frac{1}{2}u''\left[p^2 + m^2\pi - 2pm\pi\right]
\end{aligned}$$

Dividing by the marginal utility of consumption u' yields:

$$\frac{V_I - V_U}{u'} = \left[p - m\pi\right] + \frac{1}{2}\frac{-u''}{u'}\left[p^2 + m^2\pi - 2pm\pi\right]$$

In the actuarially fair case ($p = \pi m$) this collapses to:

$$\begin{aligned}
\frac{V_I - V_U}{u'} &= \frac{1}{2}\frac{-u''}{u'}\left[m^2\pi^2 + m^2\pi - 2m^2\pi^2\right] \\
&= \frac{1}{2}\frac{-u''}{u'}\left[m^2\pi - m^2\pi^2\right] \\
&= \frac{1}{2}\frac{-u''}{u'}\left[m^2\pi(1-\pi)\right]
\end{aligned}$$

C Data Appendix

Using the data sources outlined in Section 3.2, I construct two primary analytic datasets, one at the beneficiary-year level and one at the plan-year level. This section describes the construction of these analytic datasets.

C.1 Beneficiary Level Dataset

I begin by constructing a dataset of beneficiary plan choices and costs. First, I use the plan choices observed in the MBSF described in Section 3.2.1 to link individuals to plan coverage determinations described in Section 3.2.2. The combined dataset includes information on beneficiary demographics, choices, and characteristics of those choices in a given year.

I then construct measures of costs, both for the Part D plan and for the beneficiary. Using the Part D Event file, I compute individuals' total costs to the plan for a given event by summing the plan paid amount for drugs covered by the Part D benefit and drugs not covered by the Part D benefit across claims in a given year. Including both components matters for accurately measuring costs to the plans, because more generous Part D plans will, in some cases, provide coverage for drugs not covered under the standard Part D benefit. I also compute the total patient liability for a given fill by summing the patient pay amount, the low-income subsidy (LIS) paid amount, and the amount paid by third parties towards the out-of-pocket amount across claims in a given year (Research Data Assistance Center, 2024).[35] I repeat this process, splitting costs out by whether the drug on a given claim is one of the drugs approved in 2013-2014 or a drug approved a different year (based on the brand name on the claim). This allows me to divide total spending into spending on the 2013-2014 drugs and spending on all other drugs.

Finally, I link the claims-based measures of individual costs (to the plan and to the individual) to the dataset of plan choices. The resulting analytic dataset at the beneficiary level allows me to observe individuals costs, demographics, diagnoses, Part D plan choices, and detailed information about the coverage rules and characteristics (e.g. price, prior authorization, etc.) of the chosen plan. Importantly for my identification strategy, this allows me to measure whether an individual i is enrolled in a plan j with gap coverage for drug d's tier at time t. This is an important component of my analyses of plan switching and how it varies by various individual characteristics.

C.2 Plan Level Dataset

Second, I construct an analytic dataset at the plan-year level. I start by linking the coverage determinations described in Section 3.2.2 to plan characteristics. Using these combined datasets, I construct a plan-year level dataset where I observe plans' premiums, an set of indicators (one for each drug approved in 2013-2014) capturing whether the plan provides additional gap coverage on that drug's tier, and various other plan characteristics (e.g., enhanced versus basic designation,

[35] For my reduced form analyses, I exclude LIS beneficiaries (as detailed in Section 3.3), meaning that the second component is mechanically zero for my reduced form sample.

utilization management rules). In practice, plans may choose to offer partial gap coverage – that is, coverage for a subset of the drugs (e.g., non-preferred branded) on a given tier. However, data on the partial gap coverage rules is highly sparse in the data, and the data do not include details on how a plan designates a drug (e.g., as preferred versus non-preferred branded). Thus, I use the broader tier-based designation. Table 2 suggests that this captures the key issue well; high coverage plans have substantially lower out-of-pocket costs, on average, for the same set of drugs.

Next, I compute plans' raw average costs. To do so, I collapse the beneficiary-year dataset to the plan-year level. This allows me to observe average costs per enrollee for each Part D plan j in year t, as well as separate out plan costs on the 2013-2014 drugs and spending on all drugs (as constructed at the beneficiary level). I then link this dataset of plans' raw average costs and premiums by year to the public CMS data (described in Section 3.2.3) on average Part D risk score, reinsurance payments, and direct subsidy payments. The resulting dataset is an unbalanced plan-year panel that allows me to observe plans' average costs, risk-adjusted costs (constructed using raw costs and risk scores), monthly premiums, average Part D risk score, reinsurance payments, and direct subsidy payments. This is my primary analytic dataset for the plan level analyses.

D Policy Environment Details and Identification

An important identification concern is that changes to Part D that were coincident with the innovation shock – such as other policies implemented by the ACA – influenced patterns of costs and premiums during the sample period. There are a few policies to consider on this front (*Explaining Health Reform: Key Changes to the Medicare Part D Drug Benefit Coverage Gap*, 2010). First, the ACA required manufacturers to offer 50% discounts on branded drugs starting in 2011. Second, the ACA required insurers to begin paying a fraction of enrollees' drug costs in the coverage gap for generic drugs (2011) and branded drugs (2013), which would mechanically increase insurers' costs. Third, the ACA lowered the growth rate of the coverage gap and catastrophic coverage thresholds beginning in 2014, meaning that enrollees reached these phases of the benefit, where plans owed a greater share of costs, more easily.

These changes were targeted at the entire Part D market, not the small set of high coverage plans that I consider in my analysis, and so any common shocks to plans should be absorbed in the year fixed effects in the regression. Nonetheless, if the policies affected high coverage plans differently, despite being targeted at the broader market, then they could influence plan level outcomes. Thus, I consider each of these policies in turn, and I provide a few pieces of evidence that my empirical strategy indeed identifies the effects of technological change, rather than these coincident policies.

First, the implementation of manufacturer discounts began in 2011, several years before the innovation shock, and I show in the raw data that the high coverage and low coverage plans trended virtually identically for several years following these discounts before the innovation shock. Second, the policy requiring that insurers pay a fraction of enrollees' costs in the coverage gap is unlikely to explain these results for a few reasons. For generic drugs, much like the manufacturer discounts, the policy takes effect several years before the innovation shock, and the raw data and event studies show that the high coverage and low coverage plans remained on nearly identical trends immediately following the implementation of the policy. This suggests that there was little differential mechanical effect on costs. For branded drugs, plans only owed a small fraction of costs in the coverage gap in the early years of the policy (2.5% in 2013 and 2014 and 5% in 2015 and 2016), and my estimated treatment effects dwarf any mechanical changes that would have arisen from this policy change. Moreover, this policy should bias me away from finding an effect. Most high coverage plans will pay more than 2.5% of costs in the gap in 2013 and 2014 because of their gap coverage offerings, meaning the policy does not bind as strongly for the high coverage plans. Instead, the plans affected by the policy will be low coverage plans, whose costs would rise.

The final policies, the reduction in the gap and catastrophic coverage thresholds, occur in 2014. On the whole, it seems unlikely that these changes are large enough to explain the main results that I document in Section 5. First, there was little actual change in the thresholds in 2014: the threshold for gap coverage fell by $120, of which gap coverage plans pay a fraction of the costs, and the threshold for the catastrophic phase fell by just $200, of which plans pay 15% (Cubanski

et al., 2018). By contrast, I see sharp changes in costs in 2014 that are larger than any mechanical effects of this policy. Second, for high coverage plans offering additional coverage in the coverage gap, beneficiaries transitioning to the catastrophic phase has little effect on high coverage plans' liability on the margin. The reason is that the high coverage plans are already paying a larger fraction of costs in the gap, meaning that transition to the phase of the benefit where they owe 15% has relatively smaller effects (if any) on their liability. By contrast, the policy could increase costs differentially for low coverage plans that are paying less than 15% in the coverage gap and whose costs would rise as their enrollees hit the catastrophic phase more quickly. Taken together, the timing and nature of these policies suggest that they are unlikely to explain the large, sharp changes in outcomes that I document for the high coverage plans in my analysis.

E Plan Choice Model

E.1 Construction of the Choice Model Dataset

This section details the construction of the plan choice dataset. I use a random 10% sample of beneficiaries from the 5 largest PDP regions to estimate the model. This restriction is limiting but is necessary for avoiding very small cells in the fixed effects estimation while still preserving computational feasibility.

Beneficiaries choose a plan once per year during open enrollment. I start with my beneficiary-year dataset and expand it so that each individual chooses between two plans in each year: a high coverage plan H and a low coverage plan L. For each beneficiary-year choice (high coverage plan versus low-coverage plan), I compile the following characteristics.

Premiums. Plan premiums are measured directly net of rebates to the insurer and subsidies that individuals receive as a part of the LIS program. I measure subsidy amounts using public data from CMS on PDP region-by-year specific benchmark amounts.[36] I observe individuals LIS eligiblity in the MBSF, including which income band they belong to (<135% FPL, 135-140%, etc.). When collapsing to the H and L designations, I use the minimum premium for that plan type (high coverage or low coverage) in a given PDP region and year.

Measuring Out-of-Pocket Costs in Non-Chosen Plans. One challenge in my estimation is that I only observe individuals' realized out-of-pocket costs in the plan in which they enroll. In order to construct counterfactual out-of-pocket costs in the non-chosen plan alternative, I take an approach similar to Abaluck and Gruber (2011). I first group individuals into one of 1,000 cells within a given year based on their decile of total prescription drug spending, days supply, and number of prescription drug fills. I then compute the average patient out-of-pocket cost in each cell for individuals enrolled in each plan type. For each individual, I use the average out-of-pocket cost of individuals in their cell for a given plan as their expected out-of-pocket costs for each plan option in the model. I validate the approach by comparing the predicted out-of-pocket cost in plan j to realized out-of-pocket costs for individuals enrolled in plan j. In Appendix Figure E1, I show that these measures are highly predictive of realized out-of-pocket costs.

Inertia. I follow the existing literature (Shepard, 2022) in measuring inertia and construct an indicator in a given year for an individual having been enrolled in the same plan type (high coverage or low coverage) in the year prior. For this measure, new enrollees are assigned a value of 0.

[36] These data are available here: https://www.cms.gov/medicare/payment/medicare-advantage-rates-statistics/ratebooks-supporting-data.

E.2 Construction of Plan Cost Estimates

As outlined in Section 6.2, I also model individuals' costs. To do so, I closely follow the approach of Jaffe and Shepard (2020) and Kong et al. (2024).

I construct the plan cost estimation dataset using the following steps. First, starting from the plan choice dataset at the beneficiary-year dataset, I identify beneficiaries who switch between plan types (high coverage to low coverage or vice versa) during the sample period. Next, I use this switching information to construct an unbalanced panel of individuals who switch plans exactly once during the sample period (2010-2018). I drop individuals whose switch occurs in either the first or last year of the sample (and therefore have limited pre-period or post-period data). The final estimation dataset includes individuals whom I observe in different plan types in different years.

With this dataset, I estimate Equation 8. The individual fixed effects ensure that the identification of the plan effects $\theta_{j,r,p}$ is based on within-person variation over time (within a given period, pre- or post-innovation). This is also conditional on any common shocks to spending (absorbed by the year fixed effects γ_t) and individual characteristics ($X_{i,t}$) that include 5-year age bins, chronic conditions quintile, and PDP region of residence. I depart from the approach of Kong et al. (2024) in that I estimate the cost model separately in the pre- and post-innovation periods. As they note, using plan effects that take a constant form across time requires an assumption that the primary drivers of costs are unchanging. Given the reduced form evidence on the importance of technological change, however, this assumption is unlikely to hold in my setting. Allowing the plan cost effects to vary by period accommodates the possibility that the causal plan effects evolve as technology changes. Appendix Figure E2 suggests that this is likely to be the case, as the distributions of plan effects exhibit considerably more variance in the post-innovation period and the gap between the high coverage and low coverage plan effects approximately doubles.

I then construct the model-predicted costs using the plan effects estimates. The approach mirrors the setup of Kong et al. (2024), where observed individual costs are modeled as the product of an individual's cost in an average plan ($\kappa_{i,t}$) and a plan effect ($\gamma_{j,r(i)}$). Suppressing the p subscript for simplicity, we have:

$$C^{obs}_{i,j,t} = \kappa_{i,t} \times \gamma_{j,r(i)}$$

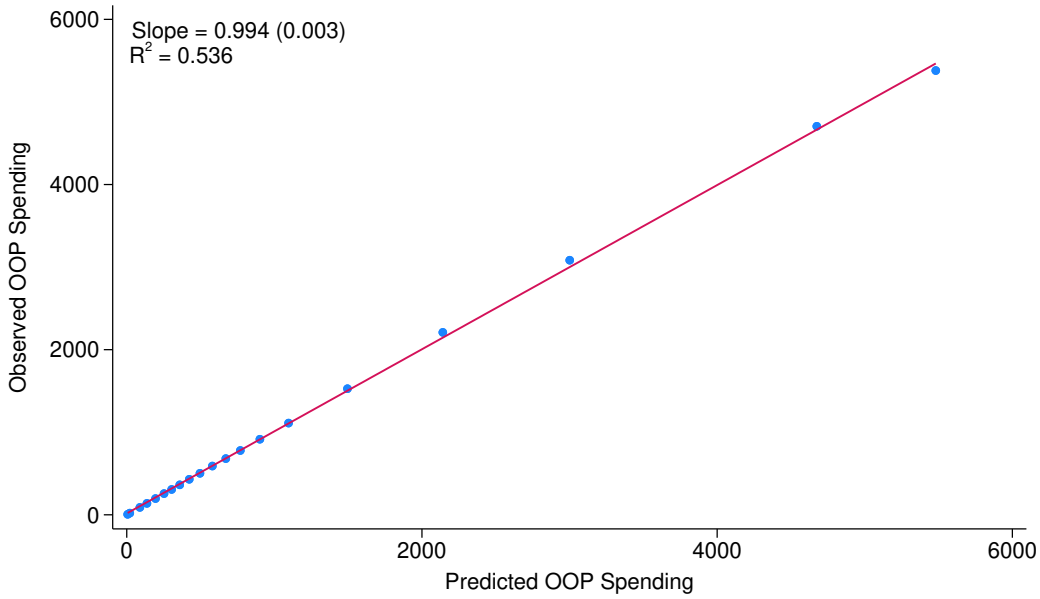
From this equation, it follows that $\kappa_{i,t} = \frac{C^{obs}_{i,j,t}}{\gamma_{j,r(i)}}$, and using this expression it is straightforward to construct costs in counterfactual plan k:

$$C^{cf}_{i,k,t} = \kappa_{i,t} \times \gamma_{k,r(i)} = \frac{C^{obs}_{i,j,t}}{\gamma_{j,r(i)}} \times \gamma_{k,r(i)} = C^{obs}_{i,j,t} \times \frac{\gamma_{k,r(i)}}{\gamma_{j,r(i)}}$$

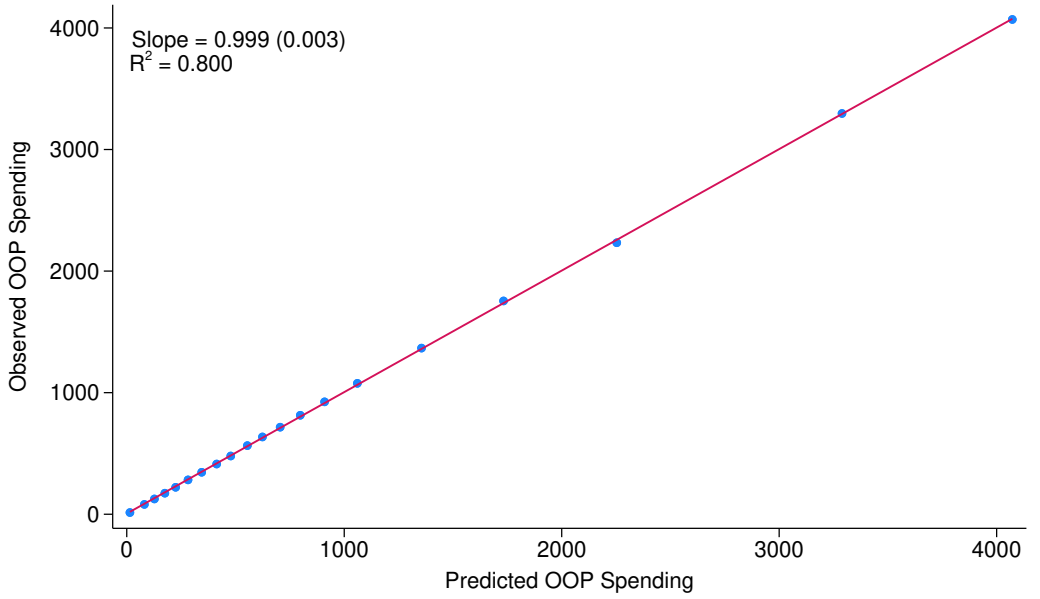
For $j = k$, the predicted costs simply collapse to individuals' observed costs.

Appendix Figure E1. Fit of Predicted Out-of-Pocket Costs

(A) L Plan



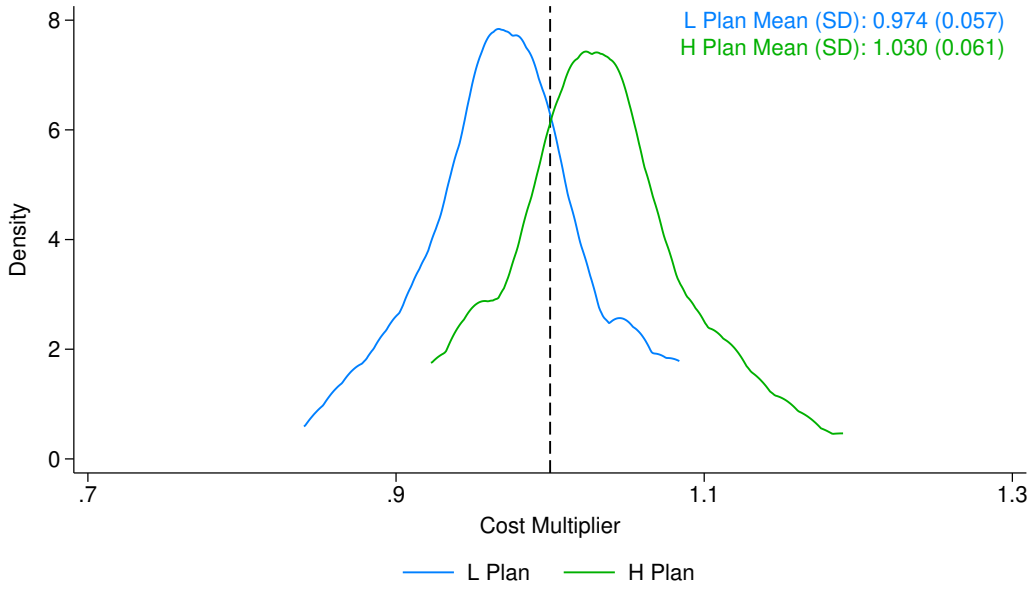
(B) H Plan



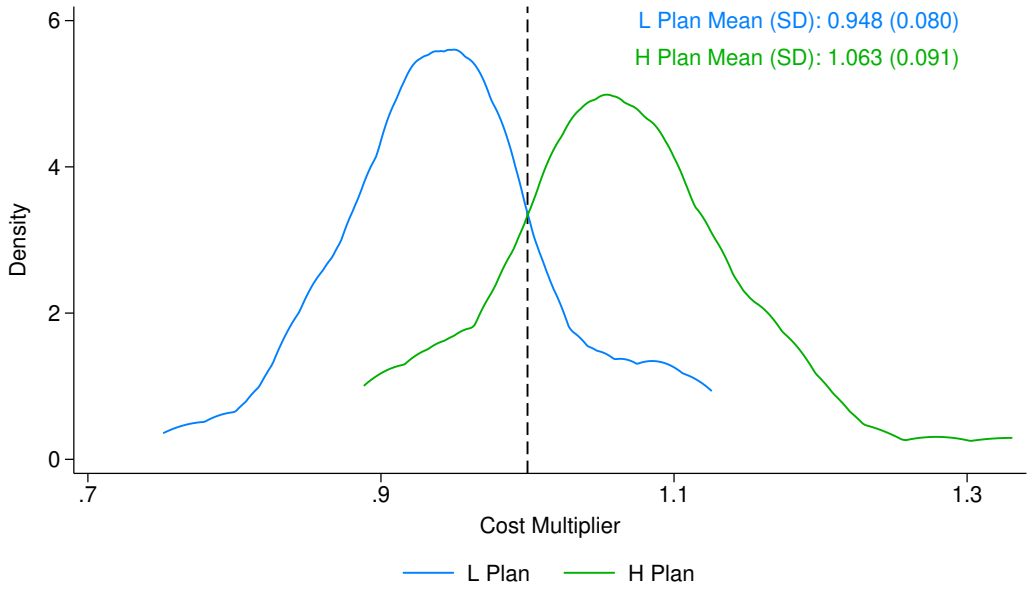
Notes: Figures show predicted out-of-pocket costs (y-axis) plotted against realized out-of-pocket costs (x-axis) each plan type. To compute predicted out-of-pocket costs, I divide individuals into 1,000 cells based on within a given year based on their decile of total prescription drug spending, days supply, and number of prescription drug fills. For each cell, I estimate out-of-pocket costs for individuals in that cell in the high coverage plans (H) and low coverage plans (L). I use the average out-of-pocket cost for an individual's cell as their predicted out-of-pocket cost in each plan.

Appendix Figure E2. Distribution of Plan Cost Effects

(A) Pre-Innovation (2010-2012)

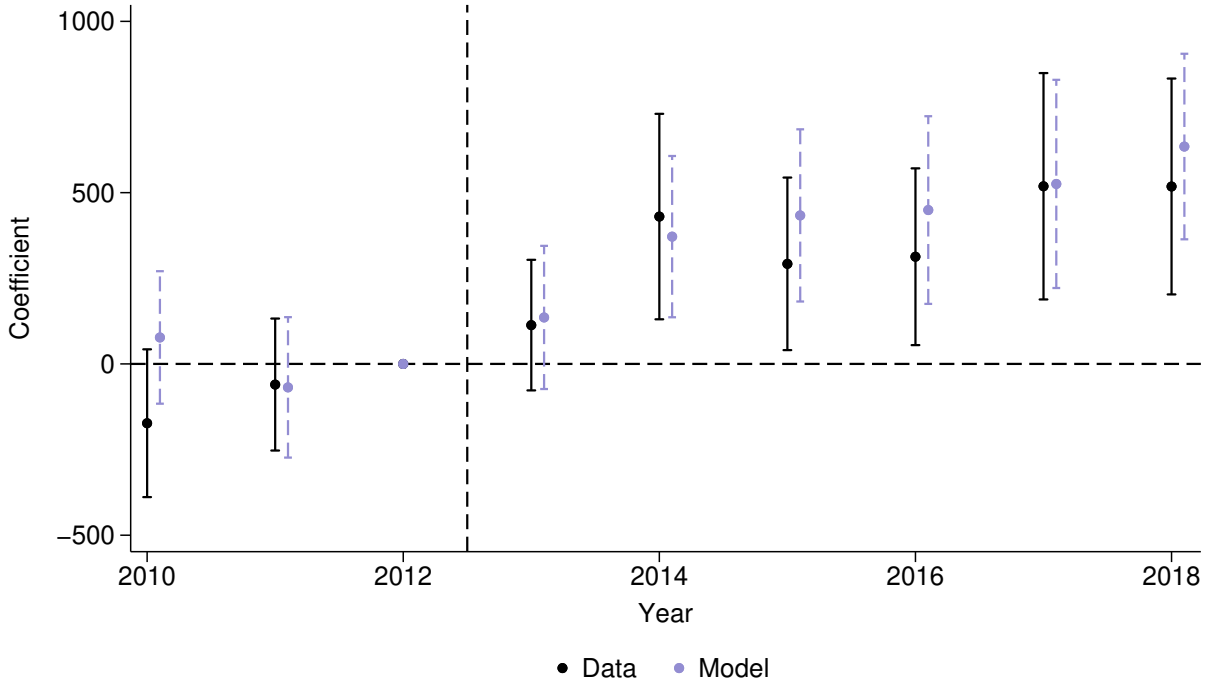


(B) Post-Innovation (2013-2018)



Notes: Figure shows the distribution of plan cost effects across PDP regions within a given period (pre- and post-2013). These effects are estimated using Equation 8.

Appendix Figure E3. Event Study, Model-Predicted versus Observed Costs



Notes: Figures shows estimates of Equation 6 at the plan type by PDP region by year level. The black coefficients show the estimates using individuals true costs and plan choices, while the purple coefficients showing individuals model-predicted costs and predicted plan shares. The patterns of model-predicted costs closely follow the reduced form patterns shown in Figure 3.

Appendix Table E1. Plan Choice Model Estimates

	Baseline		Individual Heterogeneity	
	Estimate	S.E.	Estimate	S.E.
	(1)	(2)	(3)	(4)
Premiums				
Premium	–0.00558***	(0.00040)	–0.00461***	(0.00058)
x Non-LIS			0.00019	(0.00021)
x Age 65-69			-	-
x Age 70-74			0.00126***	(0.00006)
x Age 75-79			0.00162***	(0.00007)
x Age 80-84			0.00159***	(0.00007)
x Age 85-89			0.00154***	(0.00009)
x Age 90-94			0.00166***	(0.00012)
x Age 95-99			0.00201***	(0.00021)
x Chronic Cond. Quintile 1			-	-
x Chronic Cond. Quintile 2			0.00089***	(0.00006)
x Chronic Cond. Quintile 3			0.00133***	(0.00008)
x Chronic Cond. Quintile 4			0.00158***	(0.00007)
x Chronic Cond. Quintile 5			0.00190***	(0.00007)
OOP Cost				
OOP Costs	–0.00036***	(0.00002)	–0.00040***	(0.00006)
x Non-LIS			0.00006	(0.00005)
x Age 65-69			-	-
x Age 70-74			0.00024***	(0.00004)
x Age 75-79			0.00025***	(0.00005)
x Age 80-84			0.00025***	(0.00006)
x Age 85-89			0.00017***	(0.00007)
x Age 90-94			0.00010	(0.00009)
x Age 95-99			0.00016	(0.00023)
x Chronic Cond. Quintile 1			-	-
x Chronic Cond. Quintile 2			–0.00009*	(0.00005)
x Chronic Cond. Quintile 3			–0.00002	(0.00007)
x Chronic Cond. Quintile 4			0.00000	(0.00005)
x Chronic Cond. Quintile 5			–0.00014**	(0.00005)
Inertia	4.19296***	(0.01936)	5.26934***	(0.07700)
Plan H Dummy	-	-	-	-
Plan L Dummy	0.29884***	(0.11384)	1.23215***	(0.15878)
Pseudo-R^2	0.84538		0.84966	
N	1,564,236		1,564,236	

Notes: Table shows the results from the plan choice model. All estimates use a random 10 percent sample of beneficiaries in the plan choice dataset and are restricted to the 5 largest PDP regions for computational feasibility.