Information Frictions and Adverse Selection: Policy Interventions in Health Insurance Markets*

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November 18, 2015

Abstract

A large literature has analyzed pricing inefficiencies in health insurance markets due to adverse selection, typically assuming informed, active consumers on the demand side of the market. However, recent evidence suggests that many consumers have information frictions that lead to suboptimal health plan choices. As a result, policies such as information provision, plan recommendations, and smart defaults to improve consumer choices are being implemented in many applied contexts. In this paper we develop a general framework to study insurance market equilibrium and evaluate policy interventions in the presence of choice frictions. Friction-reducing policies can increase welfare by facilitating better matches between consumers and plans, but can decrease welfare by increasing the correlation between willingness-to-pay and costs, exacerbating adverse selection. We identify relationships between the underlying distributions of consumer (i) costs (ii) surplus from risk protection and (iii) choice frictions that determine whether friction-reducing policies will be on net welfare increasing or reducing. We extend the analysis to study how policies to improve consumer choices interact with the supply-side policy of risk-adjustment transfers and show that the effectiveness of the latter policy can have important implications for the effectiveness of the former. We implement the model empirically using proprietary data on insurance choices, utilization, and consumer information from a large firm. We leverage structural estimates from prior work with these data and highlight how the model's micro-foundations can be estimated in practice. In our specific setting, we find that friction-reducing policies exacerbate adverse selection, essentially leading to the market fully unraveling, and reduce welfare. Risk-adjustment transfers are complementary, substantially mitigating the negative impact of friction-reducing policies, but having little effect in their absence.

*We thank Glen Weyl for his extensive comments on the paper. We thank Dan Ackerberg, Liran Einav, Amy Finkelstein, Avi Goldfarb, Josh Gottlieb, Matt Harding, Neale Mahoney, and Mike Whinston for their comments. We also than seminar participants at Arizona State, CEPR, CESifo, Minnesota, Princeton, UCLA, the 2015 Yale Marketing-Industrial Organization Conference, and the ASSA Annual Meetings. We thank Zarek Brot-Goldberg for outstanding research assistance. We thank Microsoft Research for their support of this work.

1 Introduction

A central goal of policy in health insurance markets is to set up an environment whereby firms will offer, and consumers can purchase, efficient insurance products that meet consumer demands for risk protection and health care provision. One key impediment to achieving this goal is adverse selection resulting from sicker consumers purchasing more comprehensive coverage and, ultimately, driving up premiums, [see e.g. Akerlof (1970) or Rothschild and Stiglitz (1976)]. The extent of adverse selection within a given insurance market can be impacted by a variety of policies including constraints on the types of contracts offered [as in the Affordable Care Act (ACA)], premium subsidies [Einav et al. (2010b)], premium risk rating [Bundorf et al. (2012), Handel et al. (2015)], mandates to purchase coverage [e.g. Hackmann et al. (2015)] and risk-adjustment transfers [Cutler and Reber (1998), Handel et al. (2015)]. Work to assess these policy options assumes that consumers have full information regarding the different aspects of their plan choice or, put slightly differently, that the choices consumers make reflect their true plan valuations that are relevant to policy analysis. However, a collection of recent empirical research on consumer choices in health insurance markets supports the notion that consumers may be far from fully informed about their health plan choices, and may have difficulties making decisions under limited information [see e.g. Handel and Kolstad (2015b), Ketcham et al. (2012), Abaluck and Gruber (2011), Barseghyan et al. (2013), Bhargava et al. (2015) and Kling et al. (2012)].[1] Accordingly, policy interventions in insurance markets to reduce consumer choice frictions such as, e.g., information provision, plan recommendations, or smart defaults are being widely considered and, increasingly, implemented [see e.g. Handel and Kolstad (2015a)].

Despite the policy relevance of information frictions and the large amount of work analyzing insurance market policies, there is still limited theoretical and empirical work systematically analyzing market policies in the context of consumers with limited information or imperfect decision making. In this paper we develop a general theoretical model that builds on prior work [Einav et al. (2010a), Spinnewijn (2015) and Veiga and Weyl (2015)] to investigate the interactions between demand and supply-side inefficiencies in health insurance markets, caused by choice frictions and adverse selection respectively. We use this framework to analyze the equilibrium and welfare implications of different policy interventions. We study two classes of competitive markets where insurers either (i) compete to offer supplemental coverage relative to a publicly provided baseline plan [see e.g. Einav et al. (2010b)] or (ii) compete to offer two types of insurance plans characterized by financial generosity [see e.g. Handel et al. (2015)] in a market with an enforced individual mandate.[2] We then use the empirical framework and estimates developed in Handel and Kolstad

[1]Past work that shows consumers may have limited information *does not* necessarily presume that consumers are making poor choices from an ex ante search perspective. It is plausible that acquiring information about health insurance given a specific choice architecture is quite costly and consumers make rational information acquisition decisions leading to limited information. Alternatively, consumers could have problems processing the information that they have or problems making information acquisition decisions.

[2]See Mahoney and Weyl (2014) for an analysis of selection markets with imperfect competition, which reverses some typical policy conclusions from competitive selection markets. See Weyl and Veiga (2015) for an in depth discussion of the equilibrium properties of the two classes of regulated competitive markets we study here.

(2015b) to show how the model can be taken to data. The model primitives are the non-parametric distributions of (i) consumer costs (ii) consumer surplus from risk protection and (iii) the impact of consumer choice frictions on willingness-to-pay.[3] For a given insurance market setup, our model maps these primitives into demand, welfare-relevant value, average cost, and marginal cost curves that permit us to characterize equilibrium price, quantity, and welfare. Under the assumptions we maintain concerning the sufficiency of these foundations for describing underlying behavior, these primitives also permit the positive and normative analysis of both demand-side policies that impact choice frictions and supply-side policies whose implications may depend on these frictions.

We begin by setting up a model to characterize how information frictions (and the policies that impact them) affect equilibrium and welfare in insurance markets.[4] We develop simple expressions to characterize the marginal impact of a policy change in terms of means and variances of the demand primitives (i.e., cost, surplus and friction value) among the marginal consumers. When frictions push the marginal consumers to demand more (less) generous coverage, a friction-reducing policy works like a tax (subsidy), which would be undesirable (desirable) when due to adverse selection equilibrium coverage is inefficiently low. In addition to this level effect on the willingness to pay, frictions also impact the sorting of consumers, (i) affecting the match between consumers and plans conditional on equilibria prices and (ii) changing the equilibria prices by changing the correlation between costs and willingness-to-pay. We prove results showing that the relationship between the underlying means and variances of consumer surplus and expected yearly costs in the population are crucial for determining whether friction-reducing policies will have positive or negative welfare impacts (conditional on a given distribution of underlying frictions). As the mean and variance of surplus rise relative to those of costs, friction-reducing policies become more attractive: the benefits of facilitating better matches between consumers and plans in equilibrium begin to outweigh the costs of increased sorting on costs and subsequent adverse selection. Conversely, as the mean and variance of costs increases relative to surplus, friction-reducing policies become less attractive. We explore these theoretical properties in a series of simulations designed to highlight these key effects.

In addition to characterizing when friction-reducing policies are 'good' or 'bad' on their own, we study how these policies interact with the supply-side policy of insurer risk-adjustment transfers. These transfers are designed to reverse adverse selection by compensating insurers who enroll ex ante sicker consumers with transfers from insurers that enroll ex ante healthier consumers and are

[3]Our analysis assumes that consumers benefit from incremental risk protection, but that there is no corresponding social benefit from reduced inefficient utilization (moral hazard), an important component of optimal insurance design that is oft-discussed in the literature. We make this assumption for simplicity: including moral hazard would increase the welfare impact of consumers enrolling in less generous coverage (and reduce the welfare impact of adverse selection) but would not impact our key positive comparitive statics related to information frictions and risk-adjustment policies.

[4]For information frictions, the space of policies we consider reduces the impact of all frictions proportionally. Alternative specifications could include informing some specific proportion of consumers or informing consumers only on one dimension. We abstract away from specific policies to inform consumers and their potential levels of effectiveness. This is in the spirit of the sufficient statistics literature where our parameters can reflect a range of underlying choice micro-foundations. We assume simply that such policies exist, and assess their impacts given their existence. See, e.g. Kling et al. (2012) for an empirical example of one such policy.

present in many different contexts (e.g. ACA exchanges, Medicare Part D, Medicare Advantage).[5] Thus, the combination of policies is a more appropriate characterization of market policies in practice than either in isolation.

We model insurer risk-adjustment transfers by allowing the insurer average and marginal cost curves to rotate as a function of the effectiveness of the risk-adjustment policy.[6] We study two features related to the interaction of friction-reducing policies and risk-adjustment policies. First, we show that in adversely selected markets increased risk-adjustment strength improves the welfare impact of friction-reducing policies, and can shift them from welfare-negative to welfare-positive. Second, we show that as friction-reducing policies become less attractive (e.g. as the potential for adverse selection increases) effective risk-adjustment plays a much more important role in increasing welfare. These results illustrate the importance of coordinating demand-side interventions with supply-side policies commonly used in insurance markets. We note that these underlying comparitive statics hold regardless of whether the market studied is for one priced supplemental plan or for two priced plans that differ in generosity. However, as shown in Weyl and Veiga (2015), the market with two priced plans is more likely to unravel in an environment with adverse selection.[7] With the insights in hand, we apply our framework to an empirical context where we can measure the distributions of surplus from risk protection, costs, and the impact of frictions on willingness-to-pay. This empirical analysis both highlights the impact the policies we study have in one context, and illustrates how to apply our framework empirically in other contexts.

We apply our framework using empirical estimates from Handel and Kolstad (2015b) who study proprietary data on the health plan choices and claims of over 35,000 employees (105,000 employees and dependents) at one large firm, linked at the individual-level to a comprehensive survey designed by the authors to measure the extent of consumers' potentially limited information on many dimensions relevant to health plan choice.[8] Using this data, the authors estimate an expected utility plan choice model that accounts for the effects of limited information on choice.

We use their estimates of risk preferences, health risk, and the impact of information frictions on choices to characterize the key elements necessary for policy analysis in our theoretical framework, including (i) consumer demand curves (ii) consumer welfare-relevant valuation curves

[5] See e.g. Cutler and Reber (1998), Brown et al. (2014) or Geruso and McGuire (2014) for discussions of risk-adjustment policies in the literature. See Kaiser Family Foundation (2011) for a discussion of these policies in the context of the ACA.

[6] Specifically, in our model the costs to the insurer for enrolling a given consumers equals that consumer's actual expected cost plus a risk-adjustment transfer that moves that cost by some proportion towards population average cost. Thus, if there are no risk-adjustment transfers then costs equal that consumer's specific expected costs to that plan, while under full risk-adjustment transfers any consumer's cost equals population average costs for that plan, from the insurer's perspective.

[7] This occurs because generous plans are forced to internalize the full costs of insuring the sickest consumers (rather than their supplemental costs) while less generous coverage cost is based on the full costs of healthiest consumers. The price difference reflects this difference in average costs, rather than the average difference in supplemental costs for those enrolling. Consequently, the market with two priced plans is more likely to unravel and friction-reducing policies are more likely to have a negative impact, while risk-adjustment is likely to be more important. The underlying relationships we study are unchanged, but a higher threshold is required for friction-reducing policies to be beneficial in the market with two priced plans. We investigate this both in simulations and in our empirical application.

[8] To protect the anonymity of the firm, we cannot reveal the exact number of employees and dependents.

and (iii) welfare-relevant and risk-adjusted cost curves. [9] While we make several assumptions to move from the large-employer context these estimates come from to the competitive counterfactual markets studied in our theoretical framework, these stylized assumptions allow us to illustrate the implications of the policy combinations we consider for market equilibria and social welfare using data and empirical estimates with appropriate depth and scope.

We estimate that consumers have a high mean ($1,787) and standard deviation ($1,304) of the impact of frictions on willingness-to-pay (pushing consumers towards more generous coverage). Expected family total costs are high, just over $10,000, as is the variance of costs, implying both high mean and variance of the cost of providing more generous coverage. The mean and variance of estimated surplus from incremental risk protection, however, are both low, reflecting low estimated risk aversion. These foundations suggest that friction-reducing policies on their own will be welfare-reducing, because the mean and variance of costs are high relative to those of surplus; informing consumers on their underlying value from insurance will increase the role of cost in decision making, exacerbating adverse selection, without substantially enhancing welfare by allocating people to the plan that gives them more surplus.

We describe our results for the class of one competitively priced supplemental policy, and note that, though more adversely selected, the market we analyze with two competitively priced policies has similar comparative statics. In this counterfactual market without any policy interventions, 85% of consumers enroll in more generous coverage with the remaining 15% in just the baseline option. This implies limited under-insurance in our stylized counterfactual environment, where 100% of consumers should enroll in more generous coverage.[10] When the impact of frictions on willingness-to-pay is reduced by 50% then 73% of consumers enroll in more generous insurance coverage in equilibrium. Removing frictions completely, however, leaves only 9% of enrollees in the generous plan. Thus, while adverse selection is still fairly limited when frictions are partially removed, in our environment fully removing those frictions substantially exacerbates adverse selection, essentially leading to the market fully unraveling. We quantify the welfare impact of these friction reducing policies, and find that the policy that reduces frictions by 50% reduces the share of first-best surplus achieved to 57% and completely removing frictions reduces that share to 15%. From a distributional standpoint, healthy consumers with frictions heavily pushing them towards comprehensive coverage gain from the friction-reducing policy, but most consumers, especially the sickest ones, lose out from the policy.

In our empirical analysis, risk-adjustment transfers are strongly complementary to friction-reducing policies, since those policies cause the market to unravel. When there is no policy in place to reduce frictions, risk adjustment transfers that are 50% (100%) effective increase cov-

[9] This empirical work drawing a clear distinction between willingness-to-pay and the welfare-relevant valuation once a product is allocated is in the spirit of recent work by Baicker et al. (2015) in health care purchasing, Bronnenberg et al. (2014) in generic drug purchasing, Alcott and Taubinsky (2015) in lightbulb purchasing, and Bernheim et al. (forthcoming) in 401(k) allocations. See Dixit and Norman (1978) for a theoretical discussion of the distinction between revealed preference and consumer welfare, in the context of advertising.

[10] While we assume away 'moral hazard' in consumer health purchasing, we note that including this would shift the welfare impacts of being enrolled in less generous coverage, but not change the nature of the positive comparative statics we study. See Brot-Goldberg et al. (2015) for a study of moral hazard in this empirical environment.

erage from 84.6% to 87.1% (88.5%), a positive, but small impact on coverage. However, when the policy to reduce frictions is fully effective, risk adjustment transfers that are 50% (100%) effective increase coverage from 9.1% to 51.6% (63.5%), with similar increases in the percent of first-best surplus achieved. We present equilibrium and welfare under the full two-dimensional space of friction-reducing and risk-adjustment policy effectivenesses, and generally show that risk-adjustment transfers are very impactful in our environment when frictions are reduced, but less impactful when they are present. Though the combined policy of fully-reduced frictions and fully-effective risk-adjustment reduces welfare slightly relative to the status quo, from a distributional standpoint there is greater equity, in the sense that there are fewer consumers leaving substantial sums of money on the table given equilibrium prices.

Our paper proceeds as follows. In Section 2 we present our theoretical framework, characterize market equilibrium and welfare and demonstrate how both are affected by demand-side and supply-side policy interventions. We also present a range of simulations designed to highlight key features of the model. Section 3 describes the data used in our analysis, and presents some simple descriptive statistics. Section 4 describes the choice model estimated in Handel and Kolstad (2015b) and its estimates. Section 5 discusses how we calibrate the model developed in Section 2 with the estimates from Section 4. Section 6 presents our empirical analysis of market equilibrium, friction-reducing policies, and insurer risk-adjustment policies. Section 7 concludes.

2 Theory

Here we develop a stylized model of the insurance market which allows us to analyze adverse selection (or supply side pricing inefficiencies more generally) and information frictions among consumers. We use our model to consider different policy options available in insurance markets to address adverse selection (e.g. risk adjustment) and information frictions (e.g. consumer choice tools). We extend the model to incorporate risk adjustment as this an important policy option considered both in theory and in practical applications (including as a part of the ACA).

2.1 Setup

Our primary model considers the case where there is a competitive market for one priced insurance plan, offered to all individuals in the market at price P. As discussed in Einav et al. (2010b), this could, e.g., reflect a market for supplemental coverage above and beyond a publicly provided government baseline coverage option. Individuals decide whether to buy the insurance plan or not. An individual i's willingness-to-pay for the plan equals w_i. The expected cost of providing the coverage depends on the individual's health risk and is denoted by c_i. Information frictions enter the model as a distortion to individual's willingness-to-pay. We denote the welfare-relevant value of the plan for individual i by v_i and the friction value by f_i such that $w_i = v_i + f_i$. An individual buys the plan if her willingness-to-pay exceeds the premium, $w_i \geq P$, while she would maximize her true utility by buying the plan if $v_i \geq P$. From a welfare perspective, however, it is efficient for her to buy insurance only if the surplus is positive, $s_i \equiv v_i - c_i \geq 0$.

Our model thus captures three sources of heterogeneity underlying the heterogeneity in insurance choices,

$$w_i = s_i + c_i + f_i.$$

Both the insurance cost c and the friction value f are inefficient drivers of insurance demand as social welfare is maximized when all individuals with positive surplus buy insurance. We assume that all variables underlying the heterogeneity are continuously distributed. The additivity of the demand components is not restrictive when we do not impose constraints on the underlying joint distribution. The model assumes that consumers have a zero price elasticity for health care spending, an oft-discussed parameter in the literature. We do this to focus the analysis on information frictions, risk-adjustment, and adverse selection: incorporating estimates on price elasticity would change the welfare numbers that result, but not the comparative statics we study.

In an expected utility framework, the value v corresponds to the difference between the certainty equivalent of facing the distribution of total expenses and the certainty equivalent of facing the distribution of out-of-pocket expenses when covered by insurance. The surplus s corresponds to the difference in risk premia with and without the plan. The friction f corresponds to the difference in willingness-to-pay as a result of, e.g., limited information or decision-biases at the time of purchase. See, e.g., Dixit and Norman (1978) for a prior theoretical framework discussing the distinction between demand and welfare-relevant value.

The model can be easily extended to a market where there are two classes of competitively priced plans (high and low coverage), as studied in Handel et al. (2015). In that case, the different demand components (surplus s, cost c and friction f) correspond to the additional coverage provided by the high-coverage relative to the low-coverage plan, as in the empirical environment we study later. We discuss this theoretical and empirical distinction further in Appendix D. See Weyl and Veiga (2015) for further discussion of the differences between these two market setups. In our context, the comparative statics we study are the same across these distinct setups, though of course actual market outcomes differ.

Demand and Ordering Individuals with different characteristics will sort into insurance depending on the price. The share of individuals buying insurance Q depends only on the distribution of the willingness-to-pay w. That is, the demand for insurance at a premium P equals $D(P) = 1 - G(P)$, where G is the cdf of w. The price elasticity of demand equals $\varepsilon_D(P) = -g(P)P/[1 - G(P)]$.

The ordering of individuals, denoted by $\mathcal{O}$, and in particular how individuals differ in their characteristics when ordered according to their willingness-to-pay, is key for the analysis. The gradient of the expected costs is crucial for the determination of the market equilibrium, while the gradient of surplus determines the welfare generated in equilibrium. The presence of information frictions affects the sorting of individuals and thus the respective gradients.[11] Similarly, any policy

[11]This approach on the demand side is also similar in spirit to ongoing work by Rees-Jones and Taubinsky (2015)

intervention that changes the ordering of individuals based on their willingness-to-pay will change the sorting of individuals into insurance and thus affect equilibrium and welfare.

We introduce the notation $E_P(\cdot) \equiv E(\cdot|w = P)$ and $E_{\geq P}(\cdot) \equiv E(\cdot|w \geq P)$ to denote the expected value among the *marginal* individuals (at the margin between buying insurance or not) and the *infra-marginal* individuals (weakly preferring to buy insurance) respectively. The expected values are conditional on the particular ordering of individuals $\mathcal{O}$.

Equilibrium Since some characteristics of individuals cannot be observed or priced by insurance companies, they care about the sorting of individuals into insurance based on their costs. In our stylized model we assume that cost c is unobservable (or unable to be priced) and insurers only compete on prices, taking all other features of the health plan as given.[12]

We focus our analysis on a competitive environment where the equilibrium price will reflect the expenses made by *all* individuals buying the health plan. That is, the insurer makes a positive profit as long as the premium P exceeds the average cost of providing insurance to the buyers of insurance at that price, $E_{\geq P}(c)$. Following Einav et al. (2010b) and Handel et al. (2015), we define the competitive price P^c by

$$P^c = E_{\geq P^c}(c). \tag{1}$$

The corresponding equilibrium coverage equals $Q^c = D(P^c)$. The analysis can be extended to imperfect competition, which introduces marginal revenues and marginal costs in the price setting [see Mahoney and Weyl (2014)]. For example, a monopolist would set the price at a mark-up above marginal costs, $P^m = \frac{1}{1+1/\varepsilon_D(P^m)} E_{P^c}(c)$.

Welfare Equilibrium welfare depends on the sorting of individuals into insurance based on surplus. We consider the total surplus (value net of cost) generated in the insurance market to evaluate welfare. This assumes that information frictions are not welfare-relevant once a consumer is allocated to a given plan, an assumption we briefly discuss in our empirical context in Section 5. This also ignores distributional consequences of policy interventions, which we consider in the empirical analysis in Section 6.

For a given ordering $\mathcal{O}$ and share Q of individuals buying insurance, welfare equals

$$\mathcal{W}(Q, \mathcal{O}) = \int_{\tilde{P} \geq P} E_{\tilde{P}}(s)\, dG(\tilde{P}) = [1 - G(P)] \times E_{\geq P}(s).$$

Changing the ordering and/or share of individuals buying insurance affects welfare generated in equilibrium.[13] For a given ordering, the surplus for the marginal buyers at price P equals $E_P(s) = E_P(v) - E_P(c)$. This marginal surplus equals zero at the *constrained-efficient* price P^{**}, taking

on tax salience.

[12] See Veiga and Weyl (2015) and Azevedo and Gottlieb (2015) for an analysis of the plan features provided in equilibrium.

[13] While equilibrium price and coverage are different under imperfect competition, the sorting of individuals remains the same. Hence, conditional on the change in equilibrium coverage, the welfare evaluation of policy interventions remains the same in other market environments.

the ordering $\mathcal{O}$ as given. For individuals who buy insurance at this price the surplus s may well be negative, while for individuals who do not buy it the surplus may well be positive. The *unconstrained* welfare benchmark with efficient sorting equals

$$\mathcal{W}^* = \Pr(s \geq 0) E(s|s \geq 0).$$

Graphical Representation In line with Einav et al. (2010b) and Spinnewijn (2015), the market equilibrium and corresponding welfare have a simple graphical representation. We can plot the demand curve $D(P)$ which orders individuals based on their willingness-to-pay and the corresponding marginal cost function $MC(P) = E_P(c)$, average cost function $AC(P) = E_{\geq P}(c)$ and (marginal) value function $V(P) = E_P(v)$. As illustrated in Figure 1, for each price P on the vertical axis, we plot the share of individuals buying insurance $Q = D(P)$ on the horizontal axis. We show the expected costs for the marginal and infra-marginal buyers and the expected value for the marginal buyers at that price P again on the vertical axis.

In an adversely selected market, individuals who are more costly to insure have a higher willingness to buy insurance. This causes the marginal cost curve to be downward sloping, as illustrated in Figure 1. The average cost curve lies above the marginal cost curve and is downward-sloping as well. Conversely, in an advantageously selected market, the cost curves would be upward sloping and the marginal cost cost curve would lie above the average cost curve. The competitive equilibrium is simply given by the intersection of the demand curve and the average cost curve.

To evaluate welfare we need the value of insurance relative to its cost and thus compare the value curve (rather than the demand curve) to the marginal cost curve. Information frictions drive a wedge between the demand curve and the value curve in two ways. For a uniform friction $f_i = \bar{f}$, the value curve is parallel to the demand curve, $E_P(v) = P - \bar{f}$. If the friction value is positive, individuals tend to overestimate the insurance value and the value curve is a downward shift of the demand curve. This is the case when all individuals overestimate the expected expenses or the coverage that is provided in the same way. Second, heterogeneous demand frictions $f_i = \bar{f} + \varepsilon_i$ cause the value curve to be a counter-clockwise rotation of the demand curve when the friction variation is independent. Individuals with higher willingness-to-pay tend to overestimate the value of insurance more while individuals with sufficiently low willingness-to-pay underestimate the insurance value despite a positive average friction. This is illustrated in Figure 1 where the average friction value $E_P(f)$ becomes negative for consumers with low willingness-to-pay.

The vertical difference between the value curve and the marginal cost curve for a given level of market coverage equals the expected surplus for the marginal buyers. Figure 1 plots the case where value always exceeds cost. Total welfare corresponds to the difference between the value curve and the marginal cost curve for all individuals buying insurance.

2.2 Policy Interventions

We consider the impact of oft-discussed insurance market policies that target (i) improving consumer choices and (ii) reducing adverse selection. We decompose the impact of the policy inter-

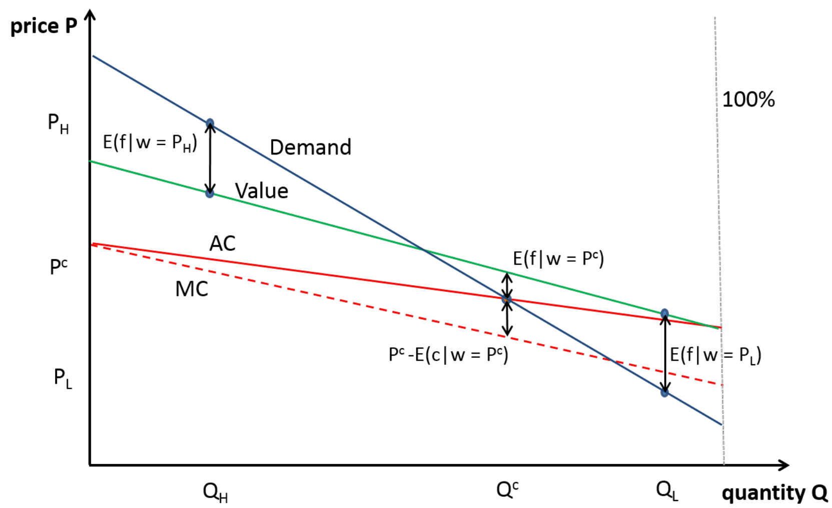

Figure 1: Demand, value and cost curves in an adversely selected market with heterogeneous frictions

ventions into two effects within our framework; a *level effect* effect conditional on the sorting of individuals and a *sorting effect* effect due to the potential re-sorting of individuals. This simple decomposition is useful both at the positive and normative level and provides a general approach for analyzing the impact of policy interventions on equilibrium outcomes and welfare.

Consider a policy variable x and the corresponding equilibrium coverage $Q(x)$ and ordering $\mathcal{O}(x)$. The first question we ask is how the policy changes the equilibrium coverage - either directly or through the re-sorting of individuals. That is, the change in equilibrium coverage equals

$$Q'(x) = \frac{\partial \tilde{Q}\left(x, \mathcal{O}\left(x\right)\right)}{\partial x} + \frac{\partial \tilde{Q}\left(x, \mathcal{O}\left(x\right)\right)}{\partial \mathcal{O}} \mathcal{O}'\left(x\right). \tag{2}$$

For example, a uniform subsidy to the price or cost of a health plan increases the share of individuals buying this plan, but won't affect the sorting of individuals. If, however, a policy affects different individuals differently it changes the sorting of individuals as well. The re-sorting into insurance based on costs will be reflected in the insurance price and thus affect the equilibrium quantity.

The second question we consider is how the policy affects welfare - either through a change in the coverage level Q or by changing sorting into insurance for a given coverage level.[14] The total

[14]Since our welfare criterion equals the total surplus, transfers between insurers and insured individuals do not affect welfare. Policies that are not budget-neutral, like a uniform subsidy, have an additional effect on welfare through their impact on the government's budget that we do not consider here. While beyond the scope of our analysis, one could extend our basic framework to incorporate the cost of public funds required to augment transfers

welfare impact of a budget-balanced change in the policy equals

$$\mathcal{W}'(x) = \frac{\partial \tilde{\mathcal{W}}(Q(x), \mathcal{O}(x))}{\partial Q} Q'(x) + \frac{\partial \tilde{\mathcal{W}}(Q(x), \mathcal{O}(x))}{\partial \mathcal{O}} \mathcal{O}'(x). \tag{3}$$

The welfare impact of changing the level of coverage simply depends on whether the policy intervention brings the equilibrium coverage closer to the efficient coverage. If the expected surplus for the marginal buyers is positive, individuals tend to be *under-insured* and the equilibrium price is inefficiently high. This underlies the analysis of price subsidies and mandates in adversely selected markets in Einav et al. (2010b) and Hackmann et al. (2015). However, these studies only considered the pricing inefficiency coming from the supply side. The presence of demand frictions may worsen the supply side inefficiency, but can also reduce this inefficiency and potentially reverse the welfare impact of an increase in equilibrium coverage, as shown in Spinnewijn (2015). The interaction between supply and demand frictions is illustrated clearly by decomposing the marginal surplus at the equilibrium price $P(x)$ as

$$E_{P(x)}(s) = E_{P(x)}(w - c - f) = [P(x) - E_{P(x)}(c)] - E_{P(x)}(f). \tag{4}$$

From the supply side, insurance companies charge prices that are different from the marginal cost in selection markets, $P(x) \neq E_{P(x)}(c)$. In a competitive market, the wedge between the average cost and marginal cost of providing insurance causes under-insurance in an adversely selected market, but over-insurance in an advantageously selected market. From the demand side, frictions cause individuals to buy coverage even if their valuation is below the price and vice versa. In particular, if the marginal buyers overestimate the insurance value ($E_P(f) > 0$), this tends to make the equilibrium coverage inefficiently high. The opposite is true if the marginal buyers underestimate the insurance value ($E_P(f) < 0$). The specific welfare impact of different scenarios depends on these offsetting effects, and which dominates.

Proposition 1 *A policy x that increases equilibrium coverage $Q(x)$ but maintains the ordering, increases welfare if and only if at the equilibrium price $P(x)$*

$$P(x) - E_{P(x)}(c) \geq E_{P(x)}(f).$$

Proof: See Appendix A

Table 1 lists all the possible cases for the competitive equilibrium of our model.[15] For example, the under-insurance due to average-cost pricing by competing insurers in an adversely selected

to achieve different levels of risk adjustment.

[15] A monopolist, however, sets the price always above marginal cost, regardless of the nature of selection. Hence, equilibrium coverage is efficiently low when the marginal friction value is negative, but can be efficiently high when the marginal friction value is positive.

Welfare Effect of Quantity Increase Competitive Equilibrium		
	$E_{P(x)}(f) > 0$	$E_{P(x)}(f) < 0$
Adverse selection	$\frac{\partial W}{\partial Q} \gtrless 0$	$\frac{\partial W}{\partial Q} > 0$
Advantageous selection	$\frac{\partial W}{\partial Q} < 0$	$\frac{\partial W}{\partial Q} \gtrless 0$

Table 1: Welfare impact of increased coverage depending on frictions and selection in the competitive equilibrium

market could be fully offset by individuals overestimating the insurance value. More generally, it makes clear that policies focused only on the supply side alone may not have their intended effects after accounting for potential demand side frictions. We turn to this later in the context of risk-adjustment transfers.

2.3 Information Policies

We first analyze the role of information frictions and how policies that target these frictions depend on the interaction of the demand and supply frictions in selection markets. Improving consumer choices has been a major concern underlying US health care reforms. Regulators and exchange operators have tackled this issues using a number of different policy tools (e.g the provision of information, the regulation and standardization of plan features, the reduction of transaction costs). In our stylized model we consider an information policy that simply reduces the impact of the demand friction f on an individual's willingness to pay. That is,

$$\tilde{w}_i(\alpha) = w_i - \alpha \times f_i$$

with $\alpha \in [0,1]$ and $\alpha = 1$ capturing the full elimination of demand frictions. An increase in α uniformly reduces the impact of frictions, but this can either increase or decrease an individual's willingness-to-pay depending on the type of friction affecting her demand.[16]

We first consider the level effect of the intervention, conditional on the sorting of consumers. An information policy increases the demand for insurance - just like a subsidy would - when the average friction among the marginal buyers $E_P(f)$ is negative. The policy works like a tax if this marginal friction value is positive. Note that even when the average friction value is positive, the marginal friction value can be negative due to the friction-based sorting of individuals.[17] Whether an information policy increases or decreases insurance demand thus crucially depends on the mean and variance of the frictions (in addition to the other primitives affecting the marginal consumers).

[16] f should be seen as sufficient for any choice policies impacting willingness-to-pay for coverage by αf_i. An extension to the model could consider heterogeneity in α for different policies as well as the underlying heterogeneity in f that we consider here.

[17] Spinnewijn (2015) analyzes this sorting effect in depth and shows that under standard conditions the marginal friction value increases in the willingness-to-pay. Hence, it is more likely to be negative when a larger share of consumers buy insurance in equilibrium.

Any policy intervention that induces more individuals at the margin to buy insurance decreases the equilibrium price in an adversely selected market (since average cost exceeds marginal cost). This further increases equilibrium coverage. In a competitive equilibrium, the impact of a simple subsidy on the equilibrium quantity is shown to be

$$\eta^c \equiv \frac{g\left(P^c\right)}{1-\left[E_{\geq P^c}\left(c\right)-E_{P^c}(c)\right]\frac{\left|\varepsilon_D\left(P^c\right)\right|}{P^c}}$$

and is thus larger in a market that is more adversely selected. Conditional on the ordering of individuals, an information policy simply scales the impact of a subsidy depending on the sign and size of the marginal friction value,

$$\frac{\partial\tilde{Q}\left(\alpha,\mathcal{O}\left(\alpha\right)\right)}{\partial\alpha}=-E_{P^c}\left(f\right)\times\eta^c.$$

For a uniform friction, this level effect would be the only impact on the market equilibrium. The welfare implication then depends on whether the insurance surplus among the marginal buyers $E_{P^c}\left(s\right)$ is positive or negative, in line with Proposition 1.[18]

With heterogeneous frictions, an information policy also changes the ordering of individuals' willingness-to-pay. In particular, the policy reduces the willingness for individuals with positive friction values to buy insurance and vice versa. Among the marginal buyers those with large friction values will have lower true values, while those with low friction values will have higher true values. Hence, a simple selection effect is underlying the re-sorting of individuals; an information policy encourages individuals with high true value to buy more insurance and discourages individuals with low true value from more buying insurance. The policy thus necessarily increases the expected true value $E_{\geq P}\left(v\right)$ for a given share of buyers. This sorting effect depends on the covariance between true value and friction value among the marginal buyers,

$$cov_P\left(v,f\right)=cov_P\left(P-\left(1-\alpha\right)f,f\right)=-\left(1-\alpha\right)var_P\left(f\right)\leq 0,$$

and is indeed always negative. The larger the variance in frictions, the more a friction-reducing policy increases the sorting based on true value. Figure 2 illustrates this sorting effect showing the combinations of true values v and friction values f for which an individual buys insurance. A downward sloping curve implied by $v+\left(1-\alpha\right)f=P$ separates the groups who buy the different plans. This curve flattens due to an information policy; individuals with high true value become more likely to buy insurance, while individuals with low true value value become less likely to buy insurance. Both changes increases the expected true value $E_{\geq P}\left(v\right)$.

As the insurance value depends on both cost and surplus, decomposing the sorting effect for costs and surplus is key. The re-sorting based on costs determines the impact on the equilibrium coverage. The re-sorting based on surplus determines the impact on welfare.

[18] If the information friction more than offsets the supply friction, $\left|E_P\left(f\right)\right|\geq\left|P-E_P\left(c\right)\right|$, the welfare gain of an information policy may be initially positive (i.e., for $\alpha=0$), but becomes negative eventually when α converges to 1 such that $\left(1-\alpha\right)\left|E_{P(\alpha)}\left(f\right)\right|<\left|P\left(\alpha\right)-E_{P(\alpha)}\left(c\right)\right|$.

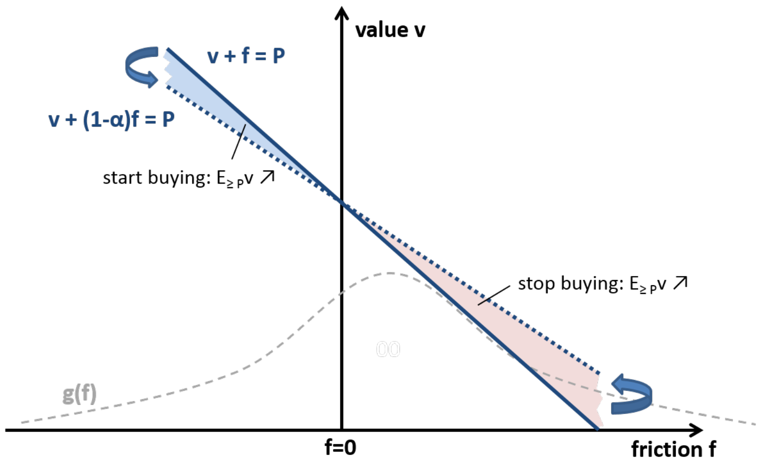

Figure 2: Sorting effect of friction-reducing policies: value and frictions among the marginal consumers

Let us consider the impact on the equilibrium coverage first. In an adversely selected market, individuals with higher true valuation have higher expenses, implying that the market becomes even more adversely selected when reducing the role of frictions.[19] This would increase the equilibrium price and thus reduce the equilibrium coverage. The total impact on equilibrium coverage from an information policy thus depends on this re-sorting on costs in addition to the change in the demand for coverage.

Proposition 2 *The impact of an information policy α on the equilibrium coverage $Q^c(\alpha)$ in a competitive market with equilibrium price $P^c(\alpha)$ equals*

$$\frac{dQ^c}{d\alpha} = -\eta^c \times [E_{P^c}(f) - cov_{P^c}(c,f)\frac{|\varepsilon_D(P^c)|}{P^c}].$$

Proof: See Appendix A

In general, the impact of re-sorting on equilibrium coverage is captured by the covariance between costs and frictions among the marginal buyers, which is indeed negative in an adversely

[19]Note that advantageous selection that is not driven by frictions (i.e., $cov(c,v) \leq 0$)) requires substantial negative correlation between surplus and cost (i.e., $cov(c,s) \leq -var(c)$).

selected market. This covariance should be compared to the average friction value among the marginal buyers to assess the impact of the policy intervention on equilibrium coverage. We further explore how the primitives of the model affect these potentially offsetting effects in simulations in Section 2.5.

Let us turn now to the impact of re-sorting on welfare. When individuals with higher true valuation have a higher surplus from buying insurance (e.g., when cost c and surplus s are independent), the average surplus of the individuals buying insurance increases when reducing the frictions. The improved matching unambiguously increases welfare, regardless of the nature of competition and whether the equilibrium coverage is efficient or not. In general, the sorting effect is captured by the covariance between the friction value and the surplus among the marginal buyers. The total welfare change then depends on this sorting effect in addition to the welfare impact from the change in coverage.

Proposition 3 *The impact of an information policy on equilibrium welfare equals*

$$\frac{d\mathcal{W}}{d\alpha} = E_{P(\alpha)}\left(s\right) Q'\left(\alpha\right) - cov_{P(\alpha)}\left(s, f\right) g^{\tilde{w}(\alpha)}\left(P\left(\alpha\right)\right).$$

Proof: See Appendix A

To evaluate the sorting effect on welfare the comparison between the relative contributions of re-sorting based on cost compared to re-sorting based on surplus induced by the information policy becomes key. Propositions *2* and *3* indicate that at the margin these effects are captured by the conditional covariance $cov_P(c, f)$ and $cov_P(s, f)$ respectively. These effects need to be compared to the level change in insurance demand captured by the mean friction value among the marginal buyers $E_{P^c}\left(f\right)$.

Corollary 1 *In a competitive equilibrium with under-insurance, $E_{P^c}\left(s\right) > 0$, the welfare gain from reducing information frictions increases in $-cov_{P^c}\left(s, f\right)$, but decreases in $-cov_{P^c}\left(c, f\right)$ and in $E_{P^c}\left(f\right)$.*

Proof: *From Propositions 2 and 3, we can simply re-write the impact on welfare in a competitive equilibrium as*

$$\begin{aligned} \mathcal{W}'\left(\alpha\right) &= -E_{P^c}\left(s\right)\eta^c\left[E_{P^c}\left(f\right) - cov_{P^c}\left(c, f\right)\frac{\left|\varepsilon_D(P^c)\right|}{P^c}\right] - cov_{P^c}\left(s, f\right) g^{\tilde{w}(\alpha)}\left(P^c\right) \\ &= -E_{P^c}\left(f\right)\eta^c E_{P^c}\left(s\right) + cov_{P^c}\left(c, f\right)\frac{\left|\varepsilon_D(P^c)\right|}{P^c}\eta^c E_{P^c}\left(s\right) - cov_{P^c}\left(s, f\right) g^{\tilde{w}(\alpha)}\left(P^c\right) \end{aligned}$$

The impact of $cov_{P^c}(c, f)$ is unambiguously positive in a market with under-insurance, $E_{P^c}\left(s\right) \geq 0$.$\square$

It is clear that due to the re-sorting of consumers, friction-reducing policies change the demand, value and cost curves and these changes depend on the underlying micro-foundations. The original demand, value and cost curves do not provide sufficient information for analyzing the market and welfare impact of such policies. However, the simple formulas in the Propositions (exploiting marginal policy changes) clearly indicate the key statistics underlying the overall effects we should anticipate. One important observation is that we can rewrite the conditional covariances (as used in the Propositions) in terms of conditional variances of the demand primitives:

$$\begin{aligned} cov_w(c,f) &= \frac{1}{2}\left[var_w(s) - var_w(c) - var_w(f)\right] \\ cov_w(s,f) &= \frac{1}{2}[var_w(c) - var_w(s) - var_w(f)]. \end{aligned}$$

This shows that the relative variance in cost and surplus underlying the demand for insurance is first-order. The higher the variance in costs relative to surplus the more likely that the increase in adverse selection dominates the increased selection on surplus in response to an information policy. This insight in our framework with consumer frictions builds on related insights in Veiga and Weyl (2015) studying equilibrium in selection markets.

The (unconditional) correlations between the different demand components matter as well because they affect the variances conditional on the willingness to pay. First, positive correlation between two demand components increases the conditional covariance between these two components. For example, positive correlation between frictions and costs will reduce the variance in costs and frictions conditional on the willingness-to-pay.[20] Second, negative correlation with a third demand component increases the conditional covariance between the first two components. For example, if individuals with higher cost have low insurance value, like in an advantageously selected market, the conditional covariance between cost and friction will be positive.

2.4 Risk-adjustment Transfers

The impact of demand frictions on equilibrium and welfare indicates their relevance for the evaluation of policies that target supply side frictions. We explore the importance of this interaction for cost subsidies and risk-adjustment transfers in particular. These policies are key features of US health reform, e.g. in the state exchanges set up under the ACA, as well as many other efforts to mitigate adverse selection and expand insurance coverage.

Risk-adjustment transfers subsidize the cost of providing insurance for an insurer based on the underlying risk of the insured individual. In practice, risk adjustment is implemented as a policy that facilitates transfers based on the realized or expected cost of the insured pool for each insurer.[21] Introducing risk-adjustment in our stylized model, the expected cost to the insurer of providing

[20] For example, in the extreme case with $c = f$, we have $cov_P\left(c,f\right) = var_P\left(c\right) = var_P\left(f\right) \geq 0$.

[21] Whether risk adjustment compensates plans based on realized versus expected cost is an important question for the efficiency of incentives to insurers that trade off selection incentives against the power of cost reduction incentives conditional on enrollment. Geruso and McGuire (2014) study the issue in detail and we abstract from this tradeoff in our model and empirical implementation.

insurance to individual i becomes

$$\tilde{c}_i(\beta) = c_i - \beta \times [c_i - Ec]$$

with $\beta \in [0,1]$ and $\beta = 1$ capturing full risk-adjustment. An increase in β makes the expected cost of providing insurance less dependent on the individual's risk type, but does not affect the ordering of individuals directly.[22] In an adversely selected market, the average cost among the infra-marginal individuals unambiguously decreases for a given price. Hence, risk-adjustment transfers unambiguously reduce the equilibrium price and increases equilibrium coverage in a competitive market. That is,

$$Q'(\beta) = \eta^c \times [E_{\geq P}(c) - Ec],$$

where η^c is the equilibrium response to a uniform subsidy.[23] The more adversely selected the market is, the larger the impact of risk-adjustment transfers on equilibrium coverage. This indicates a first key interaction with information frictions as they can reduce selection on costs. Risk-adjustment transfers will affect the equilibrium by more the less plan selection is affected by demand frictions.

Since risk-adjustment transfers preserve the ordering of individuals' willingness-to-pay, the policy affects welfare only through the change in equilibrium coverage. The impact on welfare thus depends on the surplus among the marginal buyers in line with Proposition 1. This indicates a second key interaction with information frictions as the demand and supply frictions jointly determine whether the market is under- or over-insured. In an adversely selected market where information frictions reduce under-insurance, the presence of these frictions not only reduces the effectiveness of risk-adjustment transfers in increasing coverage, but also reduces the welfare gain from that increase. The following Proposition summarizes the potential effects.

Proposition 4 *A risk-adjustment policy β increases equilibrium coverage in a competitive market by*

$$Q'(\beta) = \eta^c \times [E_{\geq P}(c) - Ec].$$

The impact on welfare equals

$$\mathcal{W}'(\beta) = E_{P(\beta)}(s)\, Q'(\beta).$$

Proof: See Appendix A

Graphically, risk-adjustment transfers will flatten the cost curves relevant to the insurer relative to the demand curve. The value curve and marginal cost curve relevant for evaluating welfare are

[22] This contrast with risk-rating where high-risk individuals pay a higher insurance premium than low-risk individuals. The analysis of the sorting effect of such policy is analogue to our analysis of information policies. Reducing the impact of costs will reduce selection based on risks, but increase selection based on frictions and on surplus.

[23] Note that in an adversely selected market risk-adjustment transfers can never decrease the equilibrium price p^c below the average cost $E[c]$ for $\beta \in [0,1]$. Hence, in contrast with a standard subsidy, it may be impossible to decentralize the (constrained) efficient allocation.

unaffected since the policy does not affect the ordering.[24]

We note that our risk adjustment framework assumes that a regulatory budget exists to fund risk adjustment transfers, and our welfare analysis does not explicitly consider the budgetary cost of the risk-adjustment policy equal to $\beta \times [E_{\geq P^c}(c) - Ec] \times Q(\beta)$. Though we do not do so here, it is not difficult to extend the model to account for different costs of funding.

This analysis highlights the important interaction between demand and supply side policies. Information policies can increase the effectiveness of risk-adjustment transfers and increase their impact on welfare. By the same token, the negative consequences of information policies through the increased adverse selection could be directly addressed through risk-adjustment transfers or any other policy that mitigates the increase in the equilibrium price. We confirm the complementarity between information policies and risk-adjustment in the simulations below.

2.5 Simulations

To provide further insights on how the different model components impact positive and normative outcomes under different policies, we present a series of simulations. We use these simulations to illustrate the role that the key micro-foundations described in this section play in determining market outcomes under (i) no policy interventions (ii) friction-reducing policies and (iii) risk-adjustment policies. Specifically, we distinguish between cases where friction-reducing interventions have positive vs. negative welfare impacts, and cases where effective risk-adjustment policies are essential prior to implementing friction-reducing policies.

Our focus is on a market setup in the mold of Einav et al. (2010b), similar to our primary model, where insurers compete to offer supplemental insurance relative to a baseline publicly provided plan. See Appendix D for similar simulations on markets with two competitively priced plans, as studied in Handel et al. (2015).

The baseline plan for these simulations has a deductible of \$3,000, with 10% coinsurance after that point, up to an out-of-pocket maximum of $\$7,000$ (this plan has a 66% actuarial value for our baseline costs below). The supplemental coverage that insurers compete to offer covers all out-of-pocket spending in the baseline plan, and thus brings all consumers up to full insurance. These plans are similar to the minimum and maximum coverage levels regulated in the state-based exchanges set up in the ACA, and also mimic the plans we study in our empirical environment later in this paper. Importantly, in our environment with risk averse consumers and no moral hazard, all consumers purchase full insurance in the first-best. In each simulation we simulate the market for 10,000 consumers.

We study a range of scenarios that vary in terms of the underlying means and variances of (i) consumer surplus from risk protection (ii) consumer costs and (iii) consumer choice frictions. Table 2 describes the underlying distributions for the different cases we study. We simulate two

[24] Note that the key difference between the uniform subsidy and the risk-adjustment transfers is that in the case of a subsidy the equilibrium is determined by a vertical shift of the original cost curves, while in the case of risk-adjustment transfers the equilibrium is determined by the original cost curves net of the risk-adjustment transfers implying rotations as discussed before.

Simulations	
Key Micro-Foundations	
Total Costs - μ_c*	5,373
Total Costs - σ_c - High*	6,819
Total Costs - σ_c - Low*	2,990
Frictions - μ_f - High**	2,500
Frictions - μ_f - Low**	0
Frictions - σ_f - High**	2,000
Frictions - σ_f - Low**	500
Risk Aversion - μ_s - High***	$1 * 10^{-3}$
Risk Aversion - μ_s - Low***	$3 * 10^{-4}$
Risk Aversion - σ_s - High***	$4 * 10^{-4}$
Risk Aversion - σ_s - Low***	$1 * 10^{-4}$

*Costs simulated from lognormal distribution.
**Frictions Simulated from normal distribution.
***Risk preferences simulated from normal distribution, truncated above 0.

Table 2: This table presents the underlying distributions of micro-foundations for the different simulation scenarios we study.

scenarios for consumer yearly expected costs: both have the same mean of just above \$5,000. The first scenario has a high standard deviation of expected costs in the population of \$6,819 while the second has a low standard deviation of \$2,990. Each scenario is generated from an underlying lognormal distribution. The within-year standard deviation in costs for a family is 3,000 plus 1.2 times their yearly expected costs in both scenarios. The impact of frictions on demand for generous insurance is generated from a normal distribution. The high (low) mean is a \$2,500 (\$0) shift in willingness-to-pay while the high (low) standard deviation we study is \$2,000 (\$500). We study all four combinations of these high/low means and variances. Finally, for consumer risk aversion, we also study four combinations from normal distributions with high/low means and variances. The high (low) CARA mean is $1 * 10^{-3}$ ($4 * 10^{-4}$) while the high (low) standard deviation is $4 * 10^{-4}$ ($1 * 10^{-4}$), with values truncated above 0. The left panel in Figure 3 shows the two distributions of costs studied. The right panel in Figure 3 shows the distribution of surplus in the market when the variance in costs is high under the cases of (i) high mean and variance of risk aversion (ii) low mean and high variance of risk aversion and (iii) low mean and low variance of risk aversion.

We first present a specific simulation example to illustrate the very different impact frictions can have on equilibrium and welfare depending on the primitives of the model. We then systematically investigate positive and normative patterns across a wider range of simulations. Our example focuses on two markets with a high variance of costs and surplus, and a low mean, but high variance of frictions. The two markets differ only in terms of mean surplus: one has low mean surplus and the other high mean surplus.

Figure 4 shows the key micro-foundations of the market with low mean surplus for the three

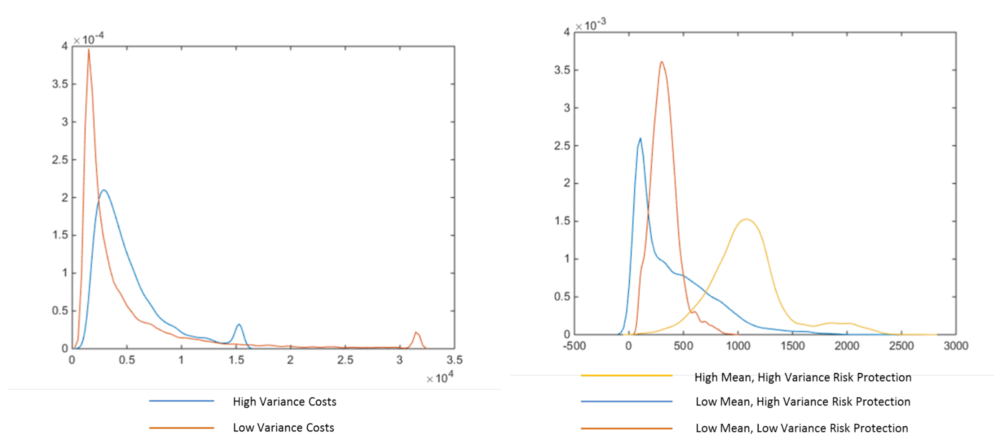

Figure 3: The left panel shows the two different cost distributions used in our simulations. The right panel shows the resulting surplus distributions under the different scenarios for risk protection, conditional on the cost distribution with high variance.

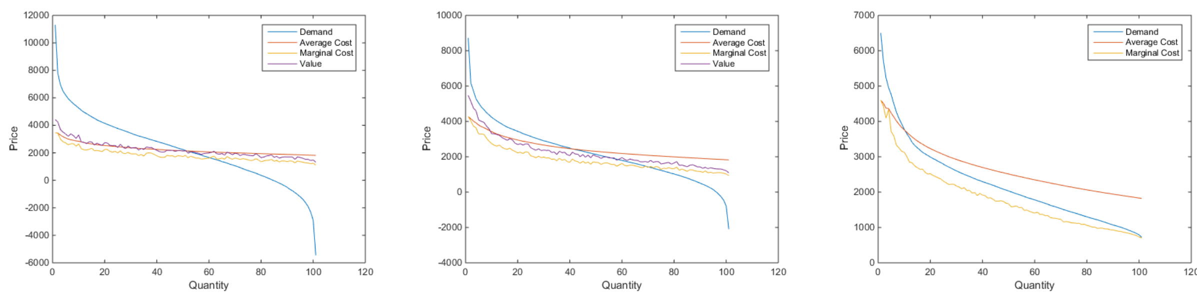

Figure 4: This figure shows the key market micro-foundations for the market with low mean surplus μ_s, in addition to high σ_s, low μ_f, high σ_f, and high σ_c. From left to right, the figure shows the three cases of (i) full frictions (ii) half frictions and (iii) no frictions.

policy cases of full frictions, frictions reduced by 50%, and no frictions. The figure illustrates a number of properties of markets with low surplus relative to costs when the variance of frictions is meaningful. When full frictions are present, the demand curve is more heavily skewed due to impacts of very positive and negative friction draws. The variance in frictions swamps the variance in costs and surplus, and the market holds together, with quantity of incremental coverage purchased equal to 0.51. When frictions are reduced by 50% ($\alpha = 0.5$) the variation in willingness-to-pay becomes much closer to the variation in costs and value, but the presence of frictions still helps hold the market together, with quantity of incremental coverage equal to 0.41. When frictions are fully removed, the market almost completely unravels, with only 11% of consumers buying incremental coverage. As the figures reveal, as frictions are reduced in this environment, the demand curve becomes less skewed, making it harder to hold the market together at the top end. Consumers with the highest willingness to pay tend to overestimate the insurance value the most and the friction reducing policy reduces their demand for insurance. In addition, as Figure 5 shows, the average cost curves become steeper as frictions are reduced, reflecting increased sorting based on costs.

Figure 6 shows the key micro-foundations of the market with high mean surplus for the same

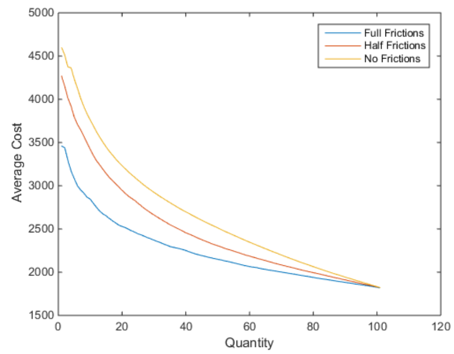

Figure 5: This figure shows the average cost curves, as a function of how much frictions are reduced for the specific simulation example with high σ_s, high σ_f, high σ_c. The mean surplus and friction do not affect this figure as they maintain the ordering of consumers.

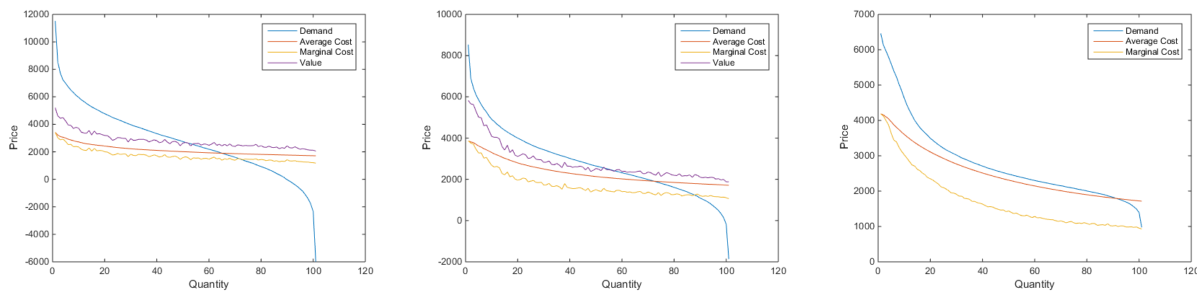

Figure 6: This figure shows the key market micro-foundations for the market with high mean surplus μ_s, in addition to high σ_s, low μ_f, high σ_f, and high σ_c. From left to right, the figure shows the three cases of (i) full frictions (ii) half frictions and (iii) no frictions.

policy interventions. In contrast to the market with low surplus, this case illustrates properties of markets where friction-reducing policies can be beneficial. In this case, when full frictions are present, 64% of consumers purchase coverage in equilibrium. Now, however, when frictions are reduced by 50%, the equilibrium percentage purchasing coverage increases to 79%, and when no frictions are present the percentage with coverage increases further to 91%. Here, friction-reducing policies have a positive impact on equilibrium coverage. As discussed before, when the share of consumers purchasing coverage is high (due to the high mean surplus), the marginal consumers tend to have a bias against purchasing more coverage. As frictions are reduced, these consumers have that bias reduced so that the demand for insurance increases. The level effect of the policy is thus positive in this market. The incremental sorting based on costs when frictions are reduced is the same as in the market with low mean surplus, but this sorting effect is now more than offset by the reverse level effect so that equilibrium coverage increases. Note that the policy not only increases equilibrium coverage, but also increases the match quality and thus will improve welfare as well (as discussed shortly).

We now investigate a broad range of scenarios corresponding to different combinations of the underlying market micro-foundations. Table 3 shows the proportion of consumers buying supplemental insurance as a function of these different micro-foundations. We explore comparative statics for different cases with full frictions present and investigate what happens when those frictions are reduced.

There are several notable patterns. First, conditional on the population distributions of surplus from risk protection s and costs c reducing the mean level of frictions (which favor purchasing generous coverage) reduces the overall demand for insurance and thus unambiguously reduces the equilibrium quantity purchased. More interestingly, following Proposition 2, it is clear that the equilibrium implications of reducing the variance in frictions very much depends on the variance of costs. Comparing the first and second columns to the third and fourth columns shows that whether σ_c is high or low has an important impact on the degree of market unraveling as the mean and variance of frictions are reduced. For example, fixing μ_s as low and σ_s as high, when the frictions mean and variance is high, the market share of equilibrium coverage is 0.92 with low σ_c and 0.91 with higher σ_c. When the frictions changes to low mean, high variance, these quantities are 0.56 and 0.51 respectively. But, when the variance in frictions is also reduced to low (along with the mean), these quantities are 0.53 and 0.17. When frictions are fully removed, 39% of consumers purchase more generous coverage for this low σ_c case, but only 11% do in this high σ_c case. Thus, when potential surplus in the market is relatively low, high σ_c implies that reducing market frictions could be especially damaging for market function.

Table 3 also confirms that the mean and variance of surplus (relative to costs and frictions) have important implications for whether frictions are 'good' or 'bad' for market function. In the cases with low σ_c, low μ_s, and low μ_f, moving from high friction variance to low friction variance has little impact on the equilibrium quantity. When μ_s and μ_f are low, but σ_c is high, moving from high to low σ_f facilitates substantial unraveling (e.g. 0.51 to 0.17 purchasing under high σ_s). However, even with high σ_c, when μ_s and σ_s are high, with low μ_f reducing the variance of frictions *increases* the equilibrium quantity from 0.64 to 0.79. The role (negative) frictions play in pushing people away from generous coverage outweighs the role that they play in reducing adverse selection through sorting.

Taken all together, these results support the earlier analysis by illustrating that (i) reducing the mean impact of frictions on willingness-to-pay for insurance always reduces insurance coverage (ii) incremental adverse selection is likely when the variance of frictions is lowered if the variance in costs is relatively high and (iii) reducing the variance and impact of frictions is good when the mean and variance in surplus are relatively high. These results are further borne out in the bottom of Table 3, which studies the same scenarios, but under the policy where frictions are completely eliminated ($\alpha = 1$). In Appendix E, in Table E4, we also present results for simulations for $\alpha = 0.5$, or partially-reduced frictions, with the comparative statics intuitively following the patterns already described here.

Table 4 presents the proportion of the first-best surplus achieved in each scenario. Notably, welfare is increasing for friction-reducing policies when μ_s and σ_s are high, but decreasing when those values are lower. The sensitivity of the relationship to the level of σ_c is substantial: when σ_c is low the market does not unravel when frictions are reduced, but when σ_c is high it unravels rather quickly and so does the surplus achieved. The welfare implications tend to be in line with the

Simulations
Equilibrium Quantities

	Low σ_c Low μ_s Low σ_s	Low σ_c Low μ_s High σ_s	High σ_c Low μ_s Low σ_s	High σ_c Low μ_s High σ_s	High σ_c High μ_s High σ_s
High μ_f, High σ_f	0.93	0.92	0.90	0.91	0.95
High μ_f, Low σ_f	1	1	1	1	1
Low μ_f, High σ_f	0.59	0.56	0.49	0.51	0.64
Low μ_f, Low σ_f	0.65	0.53	0.07	0.17	0.79
No Frictions	0.45	0.39	0.06	0.11	0.91

Table 3: This table presents the proportion of the market purchasing incremental insurance in equilibrium, for a range of underlying population micro-foundations.

Simulations
Equilibrium Surplus

	Low σ_c Low μ_s Low σ_s	Low σ_c Low μ_s High σ_s	High σ_c Low μ_s Low σ_s	High σ_c Low μ_s High σ_s	High σ_c High μ_s High σ_s
High μ_f, High σ_f	0.94	0.94	0.90	0.94	0.95
High μ_f, Low σ_f	1	1	1	1	1
Low μ_f, High σ_f	0.62	0.61	0.51	0.61	0.67
Low μ_f, Low σ_f	0.72	0.66	0.14	0.33	0.84
No Frictions	0.56	0.55	0.10	0.23	0.95

Table 4: This table presents the proportion of first-best surplus achieved in the market for a range of underlying population micro-foundations.

implications for market function: equilibrium surplus increases when equilibrium coverage increases and vice-versa. The exception holds when the variance of surplus is high relative to the variance of costs. In particular, moving from high σ_f to low σ_f (keeping μ_f low), we find that equilibrium coverage decreases, while equilibrium surplus increases. The reason is that the positive matching effect of reduced frictions outweighs the negative equilibrium consequences of any incremental selection on costs, in line with the trade-off highlighted in Proposition 3. Table E3 in Appendix E illustrates the improved matching by showing how the proportion of mistakes consumers make reduces, given the equilibrium price in each scenario. This table also highlights that while the market unraveling due to friction-reducing policies may decrease total welfare, some consumers will be better off as they now avoid making mistakes.[25]

Both the magnitude and direction of the welfare impact that friction-reducing policies have depend on how effective risk-adjustment transfers in the market are in mitigating adverse selection. Table 5 studies the interaction between friction-reducing policies and risk-adjustment policies. We

[25] This table shows, among other things, that the proportion of mistakes made in equilibrium is only related to surplus achieved in the market when the mean and variance of surplus are large relative to frictions and costs.

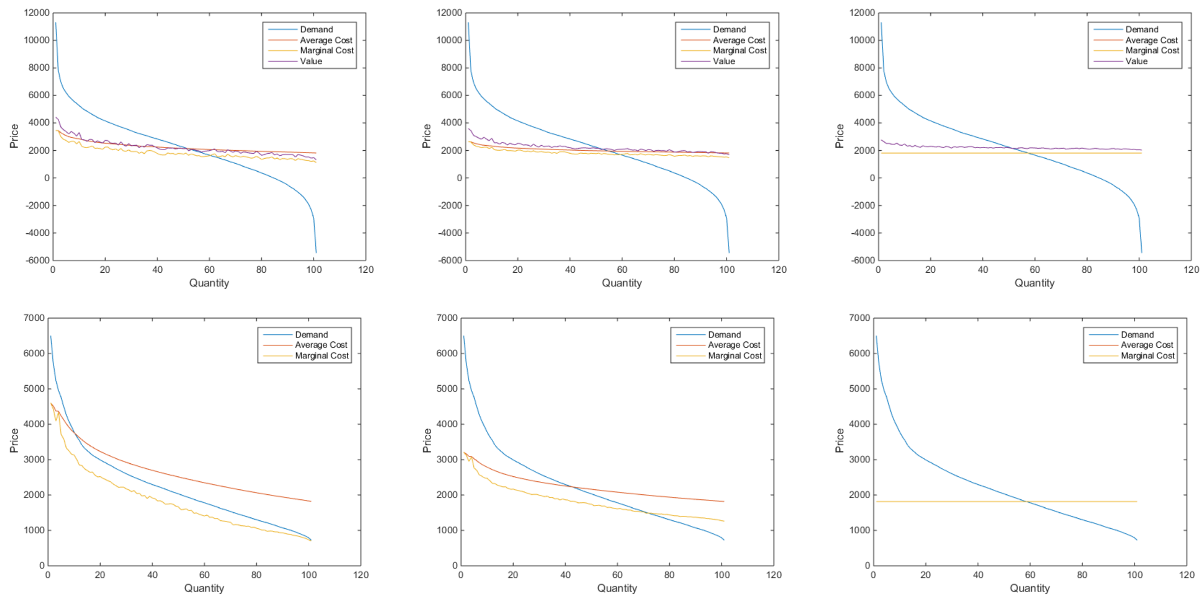

Figure 7: This figure shows market outcomes under different risk-adjustment transfer effectiveness levels. The top panel shows the impact of risk-adjustment with full frictions present, while the bottom shows the impact of risk-adjustment when no frictions are present. The market studied has high σ_c low μ_s, high σ_s, low μ_f, and high σ_f. From left to right, the figure shows the three cases of (i) no risk-adjustment (ii) partial risk-adjustment and (iii) full risk-adjustment.

use the underlying distribution of frictions with low μ_f and high σ_f for all risk-adjustment scenarios.

Consider first the case with high σ_c, low μ_s, and high σ_s. When there is no risk-adjustment the market unravels and welfare decreases as frictions are reduced. With partially effective risk-adjustment ($\beta = 0.5$), reducing frictions still reduces equilibrium quantity and welfare, but by a much lesser degree. With full risk-adjustment ($\beta = 1$), there is almost no impact of reduced frictions on quantity, and welfare increases as frictions are reduced. Thus, in this scenario, friction-reducing policies become more tenable, and switch from 'bad' to 'good' as risk-adjustment is more effective. Figure 7 shows the outcomes in this market under full frictions and under no frictions for the three different risk-adjustment scenarios studied.

Compare this now to the case with low σ_c, keeping μ_s low, and σ_s high. With no risk-adjustment reducing frictions has a slight negative impact on equilibrium quantity and welfare. With partial risk-adjustment as frictions are reduced quantity is relatively unchanged but welfare increases substantially, reflecting the impact of better consumer-plan matches. Under full risk-adjustment, both quantity and welfare are strongly increasing as frictions are reduced. Finally, column 3 demonstrates that in the case of high mean surplus for which friction-reducing policies were good for equilibrium quantity and welfare even under no risk-adjustment, this gradient increases as risk-adjustment becomes more effective. Taken in sum, as the mean and variance of surplus increase relative to the mean and variance of costs in the population, the threshold of risk-adjustment necessary to make friction-reducing policies have a positive welfare impact is decreasing.

While our analysis focuses on the case where there is one type of supplemental insurance that

Simulations Risk-Adjustment Quantity (% Surplus Achieved)			
	Low σ_c Low μ_s High σ_s	High σ_c Low μ_s High σ_s	High σ_c High μ_s High σ_s
	No Risk-Adjustment ($\beta = 0$)		
Full Frictions	0.56 (61%)	0.51 (61%)	0.64 (67%)
Half Frictions	0.57 (66%)	0.41 (56%)	0.72 (76%)
No Frictions	0.39 (55%)	0.11 (23%)	0.91 (95%)
	Partial Risk-Adjustment ($\beta = .5$)		
Full Frictions	0.57 (62%)	0.54 (64%)	0.66 (70%)
Half Frictions	0.61 (69%)	0.52 (66%)	0.75 (79%)
No Frictions	0.62 (79%)	0.42 (60%)	0.93 (96%)
	Full Risk-Adjustment ($\beta = 1$)		
Full Frictions	0.58 (64%)	0.57 (66%)	0.68 (72%)
Half Frictions	0.64 (72%)	0.59 (72%)	0.77 (81%)
No Frictions	0.71 (86%)	0.58 (75%)	0.94 (97%)

Table 5: This table presents equilibrium quantity sold, and proportion of total surplus achieved, as a function of the underlying risk-adjustment (β) and friction-reducing policies (α). The entire Table considers the case of low μ_f and high σ_f.

is competitively provided, as in Einav et al. (2010b), much of the intuition presented in this section extends to the type of market where two classes of plans with different actuarially levels are competitively offered (see e.g. Handel et al. (2015) or Weyl and Veiga (2015)). The key difference in practice between these two types of markets is that the market for supplemental coverage is less likely to unravel, because the supplemental insurer covers only incremental costs rather than the total costs of the sickest consumers. The comparative statics we study remain the same in spirit for this alternative market design: Appendix D presents simulation analysis similar to that presented in this section, but for the case of two priced classes of insurance offerings.[26]

[26]Several insights emerge. First, for a given set of micro-foundations, these multi-plan markets are much more likely to unravel. Consequently, the mean of variance of surplus relative to costs must be substantially higher for friction-reducing policies to have positive impacts in those markets, conditional on a given level of risk-adjustment. In markets with two priced plans, friction-reducing policies are always beneficial under full risk-adjustment, but, risk-adjustment must be much more effective than in the market for supplemental coverage to make friction-reducing policies welfare increasing. Thus, while the same basic intuition holds in markets with two plan types, policymakers should have a higher threshold for the effectiveness of risk-adjustment when considering the implementation of friction-reducing policies. See Appendix D for more detail on these markets, commonly referred to as exchanges.

3 Data and Empirical Setting

We now move to our empirical application, which illustrates how the micro-foundations related to frictions, surplus, and costs can be measured and used to study (i) policies that impact choice and information frictions and (ii) insurer risk-adjustment transfers. We estimate these key micro-foundations using detailed proprietary data from a large self-insured employer covering more than $35,000$ U.S. employees and $105,000$ lives overall.[27] The data include both detailed administrative data on enrollee health care claims, demographics and plan choices as well as survey data, linked to the administrative data at the individual level, on consumer information and beliefs. The linked survey data adds a novel data component that allows us to go beyond previous empirical studies and distinguish between choice determinants and preference factors that are typically unobserved to researchers. This in turn permits the positive and normative analysis of both demand-side policies that impact these frictions and supply-side policies whose implications may depend on these factors. Though our empirical analysis studies one specific environment and one specific population of consumers, it highlights how to connect the theoretical model just presented to data, and how to use those data together with an empirical framework to conduct important policy analyses.[28]

The data and econometric approach in this paper are the same as that used in Handel and Kolstad (2015b), which performs an in depth study of consumer frictions and their implications for choice modeling in health insurance markets. That paper uses the linked administrative and survey data to explore the implications of information frictions for (i) consumer choices (ii) structural estimates of risk preferences and (iii) consumer welfare. In this paper, we move beyond Handel and Kolstad (2015b) to study the implications of key market policy instruments in the presence of multi-dimensional heterogeneity in risk preferences, health risk, and choice frictions. In the next two sections, we present condensed versions of the data, model, and estimates we use, drawn from the work in Handel and Kolstad (2015b), to calibrate our model of a competitive insurance market.

Administrative Data. We observe detailed administrative data with several primary components over a four-year time period that occurs between 2008 and 2014. To preserve the anonymity of the firm, we don't provide the exact years, and we denote the four sequential years as t_1, t_2, t_3, and t_4 respectively. The data include (i) data on insurance plan characteristics and consumer choices (ii) de-identified claims data with diagnostic and financial information for all employees and dependents and (iii) demographic information and employee job characteristics (including income). Employees at the firm are relatively young ($49.7\% \leq 39$ years) and high income ($50.7\% \geq \$125,000$) relative to the general population. 51.8% of employees and dependents are male (statistics are for year t_4). 23% of employees are single, covering only themselves, with 19% covering a spouse only and 58% covering at least a spouse plus a dependent. Mean total medical expenditures for a family was $\$10,191$ in t_4. We present summary statistics, repeated from Handel and Kolstad (2015b), in

[27] We cannot reveal the exact number of employees or dependents to preserve the anonymity of the firm.

[28] One directly relevant counterfactual market is a private insurance exchange offered by the large employer we study.

Appendix E.

Over the entire period $t_1 - t_4$, employees at the firm choose between two primary health insurance options a PPO option with generous first dollar coverage and a high-deductible health plan (HDHP) with a linked health savings account (HSA). In the market and policy analysis that this paper focuses on, we maintain these two plans designs as the market offerings that insurers compete to offer and focus on policies conditional on these prescribed actuarial terms (see Section 5 for further discussion).

Table E2 (presented in Appendix E) compares the important characteristics of both plans. The PPO and HDHP have substantial differences in financial characteristics (e.g. premium, deductible, out-of-pocket maximum, HSA benefits). They are, however, identical on all other key features. The HDHP offers access to the same set of in-network providers and the same medical treatments (at the same total cost) as the PPO, both key inputs into plan value. This allows us to model relative consumer welfare from plan enrollment as a function of financial characteristics and subsequent risk exposure, rather than medical care differentiation. Financially, the PPO is the simpler and more comprehensive of the two options: it has no in-network deductible, no in-network coinsurance, and no in-network out-of-pocket maximum.[29] In contrast, the HDHP has a substantial deductible, in the range \$1,200-\$2,000 for individuals, \$2,500-\$3,500 for a couple (or parent and one child), and \$3,000-\$4,000 for a family.[30] In that plan, once an employee spends an amount in excess of the deductible, he must then pay co-insurance of 10% of allowed costs for in-network providers and 30% for out-of-network providers until his total spending exceeds the out-of-pocket maximum — between \$2,500-\$3,000 for individuals, \$4,500-\$5,500 for a couple, and \$6,000-\$7,000 for a family — at which point all expenditures are paid by the insurer.[31] Overall, the actuarial value of the PPO is close to 100% (since almost all expenditures are covered) while the actuarial value of the HDHP is approximately 78%, meaning that if all employees were enrolled in the HDHP, 78% of expenses in the population overall would be covered. Finally, the PPO plan charges no up front premium, while the HDHP provides an up-front subsidy equal to the deductible in the each tier of the plan respectively. This subsidy should be interpreted as the primary premium for the PPO relative to the HDHP.[32]

Figure 8 depicts the financial returns to selecting the HDHP option relative to the PPO option for an employee in the family tier, which has more than 50% of the employees in our sample.[33] The

[29]In the PPO employees have very limited spending for out-of-network expenditures as long as total charges don't exceed those from comparable in-network providers (exact characteristics are given in the table). Further, only approximately 4% of total expenditures are out-of-network.

[30]The exact values are the same for each employee in each coverage tier: we provide values in these fairly narrow ranges to help preserve the anonymity of the firm.

[31]Numbers are the same for each employee in each coverage tier. We provide narrow ranges here to help preserve the anonymity of the firm.

[32]The HDHP subsidy is deposited into the health savings account (HSA) linked to that plan and, thus, can be used for medical expenditures on a pre-tax basis in both the short-run and the long-run. If employees want to use the subsidy for non-medical expenditures at any point in their lives, they can do so on a post-tax basis subject to a 20% tax penalty. The linked HSA also has the potential to provide additional value to the employee, above and beyond the subsidy: employees can make incremental contributions to the HSA, on top of the subsidy, and can be used to pay for medical spending in pre-tax dollars. See Handel and Kolstad (2015b) for more detail.

[33]The same general structure holds for couples and families with shifts in the levels of the key plan terms.

x-axis plots realized total health expenditures (insurer + insuree) and the y-axis plots the financial returns for the HDHP relative to the PPO as a function of those total expenditures. For a family, the range of potential ex-post value for the HDHP spans $[-\$2,500, +\$3,750]$, with the lower bound coming from cases with a lot of medical spending, the upper bound coming from the case of zero spending.[34] Based on ex post spending 60% of employees, across all tiers, are better off financially in the HDHP, though only 15% of employees actually choose that plan. One potential explanation for this large gap is information frictions, though we require additional data to empirically identify information frictions relative to high levels of risk aversion.

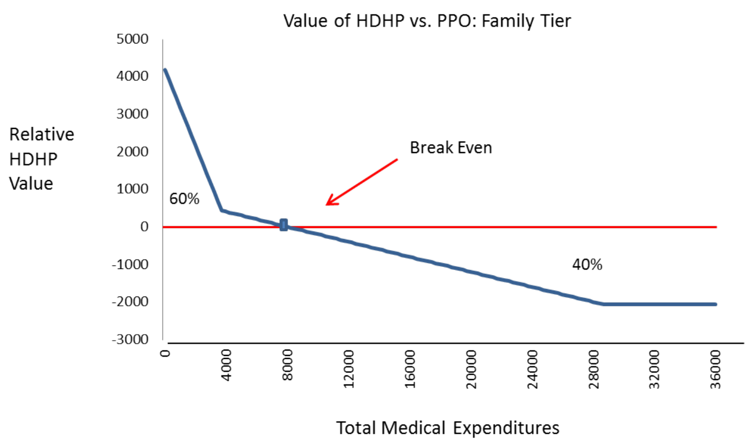

Figure 8: Description of HDHP financial value relative to the PPO in year t_4, for the family tier, as a function of total medical expenditures. This chart assumes that employees contribute 50% of the maximum possible incremental amount to their HSA, near the median in the population. 60% of *all* employees would be better of ex-post in the HDHP, given their respective coverage tiers.

Survey Data and Design. In order to measure information frictions and beliefs about non-financial plan attributes (such as time and hassle costs), we developed a survey instrument. We use the results of the survey as additional data to help quantify the impact of these factors on choices, and, in turn, the wedge they drive between consumer demand and welfare-relevant valuation. In this section we discuss the key features of the survey as it pertains to our main analysis in this paper. Section 3 and Appendix A in Handel and Kolstad (2015b) offer greater detail on the survey questions and methodology, as well as additional descriptive analysis of the link between survey responses and choices.

The survey was designed in conjunction with both the Human Resources department and the Marketing and Communications department at the employer we study. The survey was administered by the firm's insurance administrator using a clear and simple to navigate online format (see Appendix A in Handel and Kolstad (2015b) for screen shots). The insurance administrator released

[34]This range shifts upward by a constant amount if consumers derive value from incremental HSA contributions: the figure assumes consumers contribute 50% of the potential incremental contribution, up to the maximum allowed, consistent with what we find in the data. Note also that the relative value range for an individual / couple equals the family bounds multiplied by 0.4 (0.8).

the survey early in the calender year of t_4, and it remained opened for a period of two weeks, with reminders sent to the recipients just before the end of that period. The survey contained approximately thirty multiple choices questions. No incentive was given in the form of money or a prize to induce response. The survey was sent to 4,500 employees total, coming from three equal sized groups defined as (i) employees enrolled in the HDHP plan for both t_3 and t_4 ('incumbents') (ii) new HDHP enrollees in t_4 (almost exclusively people who switched from the PPO), and (iii) those in the PPO plan in both t_3 and t_4.[35] Of the 1,500 initially contacted in each group, we received response from 579 incumbent HDHP enrollees, 571 new HDHP enrollees and 511 PPO enrollees, implying an average overall response rate of 38%.

The three survey cohorts were specifically designed to over-sample the HDHP population relative to the PPO population, in order to assure enough sample size for the former and ensure sufficient statistical power. In our primary analysis, we re-weight both the survey recipients and survey respondents to reflect the actual plan choice composition in the market. [36] Throughout our analysis, when we refer to our "primary sample", we mean this re-weighted sample of survey respondents (or recipients when relevant). The last two columns of Table E present summary statistics for the randomly selected survey recipients as the well as the total survey respondents (both re-weighted as described) and compares those samples to the full sample described in the first column. The different populations are, on the whole, quite similar, mitigating sample selection concerns for the survey respondents sample. See Handel and Kolstad (2015b) for further discussion of (i) selection concerns and (ii) other concerns about the survey design (e.g. confirmation bias).

For our upcoming empirical analysis, we use the survey answers to construct measures for information frictions, as well as perceptions of time and hassle costs in plan use. We include 13 different variables derived from the survey in the vector $\mathbf{Z}$ including:

- **Information about plan financial characteristics:** We measure whether a person has correct information about HDHP plan financial characteristics. We construct a binary variable equal to 0 if a consumer knows the deductible, coinsurance rate, and out-of-pocket maximum for the HDHP and a value of 1 otherwise (implying they are at least partially uninformed). A second binary variable has value 1 when a consumer answers 'not sure' to any of these financial characteristic questions, and 0 otherwise.[37] We group knowledge of these financial characteristics together into these two variables because, as shown in Appendix D of Handel and Kolstad (2015b), the answers to these questions are quite positively correlated.

- **Provider Network Knowledge:** Our next measures study consumer information about the providers that can be accessed in network for each of the two plans. The first (second) variable has value 1 if the consumer believes that one can access more providers/services in the PPO (HDHP).

[35] Very few employees enroll in the HDHP in t_3 and switch to the PPO in t_4.

[36] This re-weighting procedure follows the econometric literature on re-weighting, which advocates re-weighting based on the dimension of explicit oversampling (in our case plan choice). For a further discussion, see e.g. Solon et al. (2013) or Manski and Lerman (1977).

[37] We include the separate indicator for 'not sure' vs. 'incorrect' because we believe these answers could be indicative of different types of misinformation.

The third equals 1 if the consumer answers 'not sure' to the question on relative provider access. The omitted case is correct knowledge that the plans provide equal access.

- **Information on Own Total Expenditures:** Our next measures study whether a person correctly understands their own total health expenditures. We categorize how an individual's answer about what their expenditures were in the prior year compares to their actual expenditures during that year. We use three indicator variables with values equal to 1 if consumers (i) overestimate (ii) underestimate or (iii) are not sure about their actual past expenditures. The omitted case is correct knowledge of past expenditures. We use this measure of past expenditure knowledge to proxy for over- or underestimation of projected expenditures for the coming year (the relevant choice object).[38]

- **Tax Benefits Knowledge:** We measure whether or not a consumer understands the tax benefits that a Health Savings Account provides (its main advantage). The first variable equals 1 if the person answers this question incorrectly, while the second one equals 1 if the person answers 'not sure.' The omitted case is the one where the person understands the tax benefits of the HSA.

- **Time and Hassle Costs:** Our final set of measures focuses on stated time/hassle costs interacted with the preferences that consumers have for avoiding them. We include a variable describing expected time spent on plan logistics / administration.[39] We interact this with variables capturing the stated preferences for avoiding these activities. A first binary variable takes value 1 if someone states that they 'strongly dislike' spending time on plan logistics / administration. A second binary variable takes value 1 if they answer they are 'concerned about but accept' some time spent on these activities. The answer 'don't care about' time spent on these activities is omitted.

Figure 9 shows the number of correct responses a given consumer in our primary sample gave to all information related questions about insurance options in the survey (all questions above, excluding hassle costs). The figure reveals that while the majority of consumers are relatively uninformed (3 or less correct out of 8 questions) there is a reasonably large tail of informed consumers as well. The variation in informativeness, as signaled via the survey responses, is a key input into quantifying the impact of frictions on demand.

4 Empirical Model

Handel and Kolstad (2015b) use the linked administrative and survey data described in the last section to estimate a choice model that quantifies (i) risk aversion (ii) health risk and (iii) the impact of information frictions on willingness-to-pay for insurance. This type of structural approach

[38] We asked the question about past expenses, rather than projected future expenses, because we believe questions about past expenditures are simpler than those about future projections. In the latter type heterogeneity in understanding the question and understanding probabilities could swamp a direct measure of under or overestimation.

[39] See Handel and Kolstad (2015b) for more detail. The answers to this question are bins of hours, e.g. "6 to 10 hours" of time and hassle costs for the upcoming year.

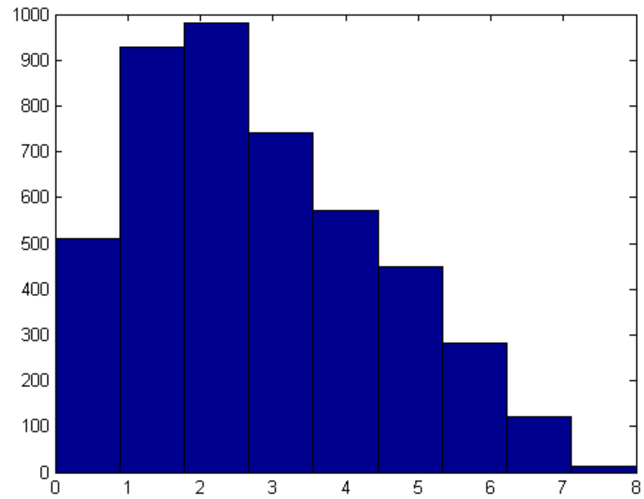

Figure 9: This histogram shows the number of correct responses a given consumer in our primary sample gave to all information related questions about insurance options in the survey. A value of 0 means that the consumer got no questions right, while a value of 8 means they got all questions correct.

is useful for assessing welfare within the current environment as well as for assessing both market outcomes and welfare in counterfactual policy environments (e.g., those where consumers choice frictions are reduced via some policies). In this section, we provide a concise description of the primary model in that paper, present its estimates, describe how these estimates determine the micro-foundations in our model and how we construct the key curves necessary for determining market equilibrium and assessing the implications of friction-reducing and insurer risk-adjustment policies.[40]

Choice Model. Our empirical specification studies expected utility maximizing families who make health plan choices that can depend on (i) *ex ante* cost risk (ii) risk preferences (iii) information frictions (iv) time and hassle costs and (v) an idiosyncratic mean zero preference shock.[41] The choice model is estimated based on employee choices for year t_4, which are the choices made concurrently to when the linked survey we use to measure information sets was conducted. We describe the model here *conditional* on our ex ante cost projections, which are estimated in a separate detailed medical cost model described later in this section and in Appendix B.

Denote the family-plan specific distributions of out-of-pocket health expenditures output by the cost model as $F_{kj}(\cdot)$. Here, $k \in K$ is a family unit, $j \in J$ is one of the two health plan options available at the firm in t_4. The baseline model assumes that families' beliefs about their out-of-

[40] Handel and Kolstad (2015b) estimate a wide range of specifications that illustrate the robustness of the primary specification we use in this paper.

[41] Consumer choices also depend on inertia, which is included in the model below. Handel and Kolstad (2015b) presents some specifications that study the relationship between inertia and information frictions, revealing that these factors are closely related but not the same (for either positive of normative predictions). Our counterfactual analysis presumes that consumers are in an active choice environment.

pocket expenditures conform to $F_{kj}(\cdot)$. Each family has latent utility U_{kj} for each plan and chooses the plan j that maximizes U_{kj}. We assume that U_{kj} has the following von Neumann-Morgenstern (vNM) expected utility formulation:

$$U_{kj} = \int_0^\infty f_{kj}(s)u_k(W_k, x_{kj}, (P_{kj}, s))ds$$

Here, $u_k(\cdot)$ is the vNM utility index and s is a realization of out-of-pocket medical expenses from $F_{kj}(\cdot)$. W_k denotes family-specific wealth and x_{kj} represents consumption in a given state of the world (defined below). P_{kj} is the family-time specific premium for plan j. Formally, in our setting we define the premium $P_{k,HDHP}$ as:

$$P_{k,HDHP} = -(HSA_k^S + \tau_k HSA_k^C)$$

HSA_k^S is the firm's subsidy to each employee's health savings account (HSA) when they enroll in the HDHP. This is deterministic conditional on the number of dependents being covered (discussed in Section 3). HSA_k^C is the incremental contribution a family makes to the HSA, on top of HSA_k^S, when they sign up for the HDHP. The value of these contributions is equivalent to the value of pre-tax dollars relative to post-tax dollars, and thus depends on marginal tax rate τ_k.[42]

Given this setup, we follow the literature and assume that families have constant absolute risk aversion (CARA) preferences implying that, for a given ex post consumption level x:

$$u_k(x) = -\frac{1}{\gamma_k(X_k^A)}e^{-\gamma_k(X_k^A)x}$$

Here, γ_k is a family-specific risk preference parameter that is known to the family but unobserved to the econometrician. We model this as a function of employee demographics X_k^A. The CARA specification implies that the level of absolute risk aversion $\frac{-u''(\cdot)}{u'(\cdot)}$, which equals γ, is constant with respect to the level of x (and, thus, W_k).

Our primary specification reduces the structural assumptions required to incorporate the impact of frictions and incorporates our survey data using a reduced form approach (see Handel and Kolstad (2015b) for a specification that treats frictions in a structural manner as well). To this end we use the indicator variables derived from survey responses, described in Section 3, as observable measures of consumer information and perceived hassle costs that imply shifts in value for the HDHP relative to the PPO. For each friction, one category (corresponding to 'no friction', e.g., 'informed') is excluded so that the value shift for the HDHP plan is relative to a frictionless consumer for the measure in question. Specifically, each included friction variable, denoted Z_f from vector $\mathbf{Z}$, shifts the money at stake for each plan, x_j, by an amount $\beta_f Z_f$ that is assumed constant across all potential health state realizations s from $F_j(\cdot)$.[43]

[42]We model HSA_{kt}^C based on actual contributions made by those who sign up for the HDHP. The model yields a family-specific prediction of incremental HSA_k^C, denoted $\widehat{HSA_k^C}$, which is inserted into the model such that $P_{k,HDHP} = HSA_k^S + \tau_k \widehat{HSA_k^C}$. Appendix E in Handel and Kolstad (2015b) discusses this model in detail.

[43]To illustrate the setup for including frictions, if variable Z_1 is an indicator variable that equals 1 if a consumer is uninformed about his deductible, then β_1 measures the difference in valuation for the HDHP plan, for an uninformed

Given this setup, for each ex post state of the world a family's overall level of consumption x conditional on a draw s from $F_{kj}(\cdot)$ is:

$$x_{kj} = W_k - P_{kj} - s + \mathbf{Z'}_k\beta\mathbf{1}_{jt=HDHP} + \eta(X_k^B)\mathbf{1}_{jt=j_{t-1}} + \epsilon_{kj}$$

Here, $\mathbf{1}_{jt=HDHP}$ is an indicator variable taking on value of one if plan j is the HDHP plan. $\eta(X_k^B)\mathbf{1}_{jt=j_{t-1}}$ captures the impact of inertia distinctly from the impact β of information frictions: empirically, inertia is identified separately from the active choice impact of information frictions by comparing the choices between new employees, who make active plan choices by definition, and existing employees who have a default option and may be impacted by inertia.[44] Finally, ϵ_{kj} is a family-plan specific idiosyncratic preference shock that is assumed to be mean zero in estimation. Subject to this model, families choose the plan j that maximizes U_{kj}.

We now briefly discuss the cost model, identification, and estimation, before presenting the model estimates.

Cost Model. The empirical choice framework takes consumer expectations of future out-of-pocket expenditures for each family, $F_{kj}(\cdot)$, as given. At a high-level, the cost model is intended to estimate the full information, ex ante distribution of out-of-pocket expenditures for each family. Appendix B presents a detailed description and discussion of the cost model and the family-level estimates of $F_{kj}(\cdot)$ that are used as inputs into the choice model.

The cost model assumes that there is no private information (beyond the information used in our cost model) and no moral hazard (total expenditures do not vary with j). While both of these phenomena have the potential to be important in health care markets, and are studied extensively in other research, we believe that these assumptions do not materially impact our choice model estimates. This is true because (i) both effects are likely to be quite small relative to consumers' total relative valuations of the two plans and (ii) the data contain a lot of detail on consumer medical conditions. Importantly, it is also possible that individuals know *less* about their risk profile than we do, which we address to some extent in our model with dummy variables derived from our survey data on consumer beliefs about past spending (and how those beliefs compare to actual spending). See Handel and Kolstad (2015b) for estimates from a model that structurally integrates consumer biases in beliefs about total spending. See Handel and Kolstad (2015b) for a more in depth discussion of why both private information and moral hazard are unlikely to bias our choice model estimates in any meaningful way.

Identification and Estimation. They key quantities we separately identify are (i) risk preferences (ii) health risk and (iii) the impact of frictions on willingness-to-pay and (iv) inertia. Since

person, relative to an informed person. The coefficient β_1 is a reduced form measure that represents the implications of an underlying model of choice under uncertainty with limited information, similar to that presented in Section 2 in Handel and Kolstad (2015b).

[44]This model for inertia assumes that inertia operates similar to a tangible switching cost. Alternatives to this approach could include (i) a two-stage rational inattention model or (ii) an endowment effect model. See Handel (2013) for an extended discussion of different models of inertia.

our focus here is to use our estimates to calibrate the demand, welfare-relevant value, and cost curves to study policies in competitive insurance markets, we refer the reader to the highly detailed discussion of identification in Section 4 of Handel and Kolstad (2015b).

We also include the details of our estimation algorithm in Appendix C. There are two key paramaterizations to point out here. First, we assume that the random coefficient γ_k for risk preferences is normally distributed with a mean that is linearly related to observable characteristics X_k^A:[45]

$$\begin{aligned} \gamma_k(X_k^A) &\quad \to N(\mu_\gamma(X_k^A), \sigma_\gamma^2) \\ \mu_\gamma(X_k^A) &\quad = \mu + \delta X_k^A \end{aligned}$$

In the primary specifications X_k^A contains employee age, gender, and income. Second, we assume that the inertia term, $\eta(X_k^B)$ is related linearly to demographics X_k^B:

$$\eta(X_k^B) = \eta_0 + \eta_1 X_k^B$$

X_k^B includes income, age, gender, and family insurance coverage tier dummies (corresponding to single, plus one dependent, or two or more dependents).

Model Estimates. Table 6 presents the results of the choice model.[46] Column 1 presents the point estimates and column 2 presents the bootstrapped 95% confidence intervals.[47] For risk preferences, in addition to providing the estimated CARA parameters, the table also provides a simpler interpretation for expositional purposes. The row labeled 'Gamble Interpretation of Average μ_γ' presents the value X that makes a consumer indifferent between the status quo (accepting no gamble) and accepting a gamble where he wins $\$1,000$ with 50% chance and loses $\$X$ with 50% chance. Thus, if $X = 1,000$, the average consumer is risk neutral, whereas if $X = 0$, the average consumer is infinitely risk averse. In what follows when we refer to "gamble interpretation" we are referring to this value of X.

For risk preferences, in the full model we estimate a mean gamble interpretation of $X = 920.47$ with confidence interval $[822.51, 924.23]$. This suggests some risk aversion, but generally low mean risk aversion relative to the literature (see e.g. Cohen and Einav (2007) or Handel (2013)).[48] In addition, there is a low degree of heterogeneity in risk preferences, represented both by unobserved heterogeneity (σ_γ) and observable heterogeneity that shifts μ_γ. The low mean and low variance of population risk aversion suggest that surplus from risk protection provided by incremental insurance

[45] We assume that γ is truncated just above zero, at 10^{-15}, though this is generally non-binding.

[46] Handel and Kolstad (2015b) presents many other specifications, designed to assess the implications of including friction measures in a structural setup and designed to assess robustness of our primary specification.

[47] The methodology for computing these standard errors is presented in detail in Appendix C.

[48] As shown in Handel and Kolstad (2015b), the inclusion of information frictions and hassle cost measures has a economically meaningful and statistically significant impact on risk preference estimates, which is one key reason why, in our context, the estimates reveal less risk aversion than prior work that omits such additional factors.

will have a similarly low mean and variance in our upcoming market analysis.

The coefficient estimates on each friction can be interpreted as the average impact of each on consumer willingness-to-pay for incremental insurance. Consumers who believe that the PPO plan has a larger network of medical providers value the HDHP by $2,326 less than someone who correctly knows that these plans grant the same access (significantly different from 0, 95% CI upper bound of -$1,286). Those who underestimate their own total medical expenditures for the past year value the HDHP by $208.30 less than those with correct information while those who overestimate their expenditures prefer the HDHP by $62.98 relative to the fully informed (counter-intuitively). Though the point estimates are wrong signed they are not statistically different from zero. Interestingly, those who answer "not sure" to this question value the HDHP by $688.91 less on average: this may reflect the fact that those who answer "not sure" have a deeper lack of information that causes them to choose the PPO, though there are other potential micro-foundations for this.

Those who answer any of the three main questions on HDHP financial characteristics incorrect actually prefer the HDHP by $98.04 relative to those who get all of these questions correct, while those who answer "not sure" to any of these questions have -$467.48 lower relative average valuations. These effects also have fairly wide 95% CIs that include 0.[49] Finally, stated time and hassle cost quantities and preferences have a substantial impact on choices. For *each* additional stated hour of time spent on plan billing, administration, and logistics, a consumer with a strong dislike for hassle costs values the HDHP by $138.70 less. If a consumer "accepts but is concerned about" time and hassle costs, they value the HDHP by $127.87 less per stated hour. These are relatively precise estimates: the upper bounds on the 95% CIs for these coefficients are -$79.74 and -$65.51 respectively. For the median individual in the sample, who expects to incur between 6 and 10 hours of time and hassle costs, this implies (taking the midpoint of 8 hours) a $\$138.70 * 8 = \$1109.60$ drop in utility for the HDHP plan if they state they have a strong dislike for hassle costs. Reassuringly, those who state that they are "not particularly concerned about" time and hassle costs have a coefficient estimate of $9.72 less per stated hour which is statistically indistinguishable from 0.

Key Micro-Foundations. Our data and estimates provide all of the key consumer micro-foundations that we need to calibrate the insurance market equilibrium model described in Section 2. Figure 10 presents the smoothed distribution of the combined impact of all frictions on willingness to pay for less generous coverage relative to more generous coverage. This is the empirical analog to the distribution of f from Section 2 and describes how much the frictions present shift willingness to pay relative to a frictionless consumer. The figure plots this distribution for families (employees covering 2+ dependents), who comprise the majority of our primary sample. As the figure illustrates, the distribution of f here has a high mean impact of shifting consumers towards

[49] While frictions with respect to total medical expenditure knowledge and plan financial characteristic knowledge both have imprecisely estimated coefficients near 0 in the full model, in the models with just one friction measure included, shown in Handel and Kolstad (2015b), the coefficients for these frictions are negative and large in magnitude, implying a distaste for the HDHP as expected. This suggests that these frictions do imply lower utility for the HDHP plan on their own, but, are correlated with other friction measures presented in the full model, and overpowered by those frictions in that model.

Primary Model Estimates	Model Estimate	95% CI
Average μ_γ	$8.6 \cdot 10^{-5}$	[$8.19 \cdot 10^{-5}$,$2.23 \cdot 10^{-4}$]
Std. Dev. μ_γ	$1.4 \cdot 10^{-5}$	[$9.41 \cdot 10^{-6}$,$4.41 \cdot 10^{-5}$]
Gamble Interp. of Average μ_γ	920.47	[822.51,924.23]
σ_γ	$2.2 \cdot 10^{-9}$	[$5.98 \cdot 10^{-6}$,$1.55 \cdot 10^{-4}$]
σ_ϵ, HDHP	0.11	[1.58,666.04]
Benefits knowledge:		
Any incorrect	98.04	[-614.70,377.52]
Any 'not sure'	-467.48	[-1670.66,127.94]
Time cost hrs. X prefs:		
Time cost hrs.	-9.72	[-90.07,118.86]
... X Accept, concerned	-118.15	[-282.81,-55.79]
... X Dislike	-128.98	[-293.99,-70.02]
Provider networks:		
HSP network bigger	-594.38	[-1842.45,562.52]
PPO network bigger	-2362.85	[-3957.68,-1286.62]
Not sure	-201.81	[-937.44,303.21]
TME guess:		
Overestimate	62.98	[-810.72,704.28]
Underestimate	-208.30	[-1154.63,837.19]
Not sure	-688.91	[-1987.28,320.99]
Average Friction Effect	-1787.40	[-2148.63,-906.96]
σ Friction Effect	1303.64	[1264.29,2329.12]
Likelihood Ratio Test Stat for Frictions	379.54	

Table 6: This table presents our primary estimates of our empirical choice framework. The first column presents the actual point estimates while the second column presents the 95% CI derived from the bootstrapped standard errors. Here, positive friction values indicate greater willingness-to-pay for high-deductible care.

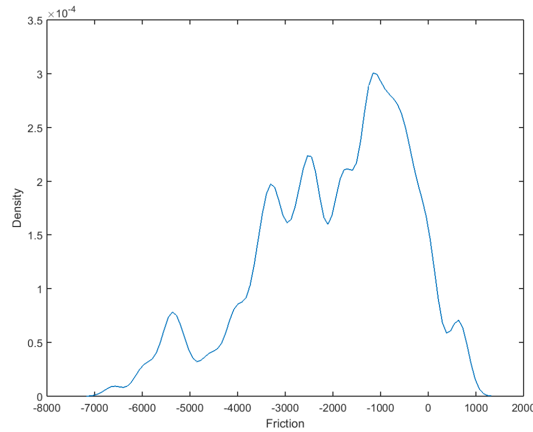

Figure 10: This figure presents the smoothed distribution of the total impact of frictions on willingness-to-pay for high-deductible coverage (the lower tier of coverage offered) using our estimates from the choice model. This chart presents the estimates for families (employees covering 2+ dependents), who comprise the majority of our sample are who are the focus of our upcoming counterfactual market analysis.

more generous coverage (\$1787, see Table 6) as well as substantial heterogeneity (standard deviation of \$1304.[50] Thus, our empirical environment corresponds most closely to the case with high mean friction impact and high friction heterogeneity presented in Section 2.

Figure 11 plots the distribution of expected total spending for families in our primary sample: as is typical this is a fat-tailed distribution similar to a lognormal distribution with a fairly large degree of consumer heterogeneity and a high level of mean spending. Based on this, we calculate the expected supplemental cost to an insurer from providing PPO coverage rather than HDHP coverage, which is the empirical analog to c in Section 2.

Figure 12 presents the distribution of surplus from risk protection for the PPO relative to the HDHP, the empirical analog to s in Section 2. The distribution of surplus is skewed towards 0, since many consumers are estimated to be near risk-neutral, though there is a non-trivial group of consumers with substantial positive surplus.[51] Overall, the mean and variance of this surplus are substantially lower than the means and variances of the cost distribution and the friction distribution.

Figure 13 brings these elements together and presents the distribution of willingness-to-pay for the PPO relative to the HDHP in the observed environment, the empirical analog to w in Section 2. Consumer willingness to pay for the PPO, which determines the demand curve in our upcoming analysis, is large and heterogeneous primarily due to the impacts of consumer costs and how frictions impact willingness-to-pay.

[50] As Table 6 shows, the lower bound on the 95% confidence interval for the mean population friction impact is 906.96, well above 0.

[51] In the next section, as an additional example, we also investigate the implications of baseline model estimates from Handel and Kolstad (2015b) which omit friction measures and show substantially larger risk aversion and consumer surplus.

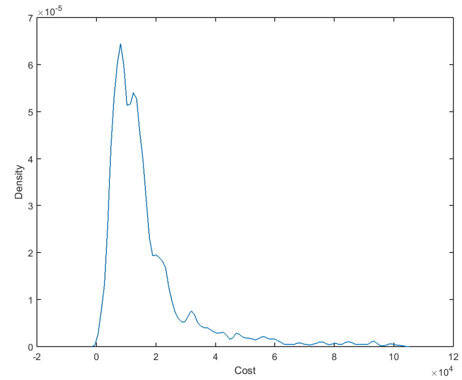

Figure 11: This figure presents the smoothed distribution of expected costs from the cost model for families in the primary sample. These costs are fully covered by the PPO and only partially by the HDHP.

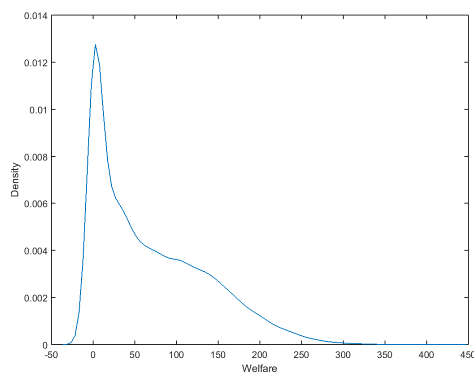

Figure 12: This figure presents the smoothed distribution of the surplus from risk protection from the PPO relative to the HDHP for families in the primary sample, given our primary estimates.

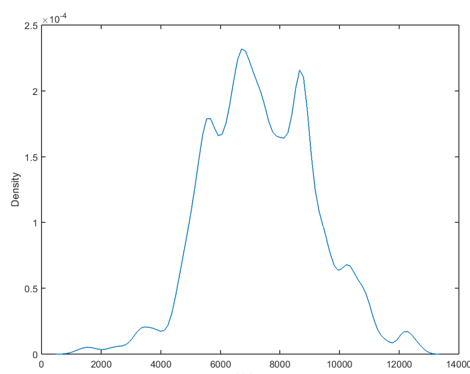

Figure 13: This figure presents the smoothed distribution of consumer willingness to pay for the PPO relative to the HDHP, for families in the primary sample, given our primary estimates.

Correlations					
Key Micro-Foundations					
Primary Estimates					
	Friction f	Surplus s	Cost c	WTP	Value
Friction f	1	-0.0082	0.0249	0.8485	0.0269
Surplus s	-0.0082	1	0.8418	0.4418	0.8211
Cost c	0.0249	0.8418	1	0.5075	0.9993
WTP $(f + s + c)$	0.8485	0.4418	0.5075	1	0.5062
Value $(s + c)$	0.0269	0.8211	0.9993	0.5062	1

Table 7: This table presents key correlations between (i) impact of frictions on PPO willingness to pay (ii) incremental surplus from PPO risk protection (iii) expected marginal PPO health spending for insurer (iv) willingness to pay for PPO and (v) true relative PPO value. Results are presented for families (covering at least a spouse and dependent) who comprise over 50% of our primary sample.

Table 7 presents the correlations between these micro-foundations for families in our primary sample. The first thing to note is that the impact of frictions is relatively uncorrelated with surplus from risk protection, cost, and true value for more generous coverage. It is highly correlated with willingness-to-pay, since frictions are large in magnitude and feed directly into willingness-to-pay. Surplus from risk protection is highly correlated with cost and with true plan value, but less correlated with willingness-to-pay due to the presence of frictions. Cost is almost perfectly correlated with true value, because of limited heterogeneity in risk aversion, while frictions are the strongest correlate of willingness-to-pay. Taken in sum, these results suggest that frictions are an important determinant of demand in our environment, as are costs, and that costs become much more highly correlated with willingness-to-pay when frictions are removed.

5 Market Setup

The primary counterfactual market we consider is, as described in Section 2, a competitive market for supplemental insurance that moves consumers from universal baseline coverage (represented by the HDHP in our empirical environment) to more generous overall coverage (represented by the PPO). We assume that an individual mandate is enforced, such that individuals enroll in either the public baseline coverage, or that coverage plus the supplemental coverage (for this market, this is similar to saying the public coverage is provided for free). This section describes how we use our model estimates just described to construct the key objects sufficient for policy analysis, as outlined in Section 2.

We make several important assumptions to translate our estimates into these key objects. First, we assume that consumers make active choices and have no default option (i.e. no inertia). Second, we assume that the relative information frictions we estimate for our two empirical plans map directly to the relative information frictions that consumers have for supplemental coverage relative to the baseline coverage. This assumption would be violated, e.g., if competing insurers worked harder to either provide or obscure information relative to what the firm in our empirical environment does. This analysis should thus be viewed as a stylized analysis that highlights the potentially nuanced implications of friction reducing policies together with risk-adjustment policies, rather than an analysis that makes specific predictions of what will happen in a particular regulated marketplace.

In Appendix D, we also present some results for the class of markets studied in Handel et al. (2015) where insurers compete to offer two types of insurance policies simultaneously and an individual mandate is in place requiring consumers to buy one of the two types of policies. Construction of demand and value for incremental coverage is the same as in the primary markets studied in the main text, but construction of average and marginal cost curves is different, reflecting the internalization of costs by the lower coverage plans in that setup.

Demand, Value, and Cost Curves. We study a range of demand-side policies that reduce consumer choice frictions and supply-side policies that impact the costs insurers face for different consumers. Using our structural estimates of frictions, surplus and costs we construct (i) demand curve (ii) welfare-relevant value curve and (iii) average and marginal cost curves for each policy scenario.

The demand curve reflects consumer willingness-to-pay for more generous coverage in a given policy environment. This willingness-to-pay is the same regardless of whether it is a market for supplemental add-on coverage or a market where insurers offer both types of plans. Of the two policies we consider here — those that reduce information frictions and insurer risk adjustment transfers — only the former impacts consumer demand. As a result, counterfactual consumer willingness-to-pay for each plan j given a specific information friction reduction policy α is:

$$\begin{aligned}
\widehat{U_{kj}}(\alpha) \quad &= \int_0^\infty \widehat{f_{kj}}(s)\frac{-1}{\gamma_k(X_k^A)}e^{-\gamma_k(X_k^A)\widehat{x_{kj}}(\alpha,s)}ds \\
\widehat{x_{kj}}(\alpha,s) \quad &= W_k - P_{kj} - s + (1-\alpha)\mathbf{Z'}_k\widehat{\beta}\mathbf{1}_{j_t=HDHP} + \widehat{\eta(X_k^B)}\mathbf{1}_{j_t=j_{t-1}} + \hat{\epsilon_{kj}}
\end{aligned}$$

Thus, when $\alpha = 0$ all information frictions are present and consumer demand is composed of estimated willingness-to-pay for each plan in our given environment. When $\alpha > 0$ then information frictions are reduced by some fraction, up to the case when $\alpha = 1$ and 100% of frictions are removed. In our upcoming analysis, we investigate a space of policies corresponding to values of α between 0 and 1. The level of α can be thought of as a reduced form representation of different policy combinations that reduce consumer choice frictions (e.g. information provision, decision support, or smart defaults). Though we do not quantify the empirical impact of actual friction-reducing policies in this paper, one could in principle study values of α linked to specific empirical measures and/or policy changes.

We define willingness-to-pay for the PPO, relative to the HDHP, as the difference in certainty equivalents implied by the above utility model:

$$w_k(\alpha) = \widehat{CE_{k,PPO}}(\alpha) - \widehat{CE_{k,HDHP}}(\alpha) \quad (5)$$

Here, w_k is family k's relative willingness to pay, and $CE_{k,x}$ is the certain financial payment that gives equivalent utility to that families' utility from choosing plan x.

The corresponding relative demand curve reflects willingness to pay for the PPO relative to the $HDHP$ given the friction-reducing implications of α:

$$D(P;\alpha) = Pr(w_k(\alpha) \geq P)$$

Here, P is the price of supplemental coverage that moves the consumer from the baseline HDHP plan to combined coverage represented by the PPO plan. We use this demand curve for our equilibrium analysis of counterfactual policies with specific values of α.

Denote by v_k the value of additional coverage in an environment with no information frictions (i.e., $v_k = w_k(1)$). The welfare-relevant value curve $V(P;\alpha)$ reflects v_k conditional on *the same ordering* of consumers as $D(P;\alpha)$:

$$V(P;\alpha) = E[v|w_k(\alpha) = P]$$

The empirical value curve only coincides with the demand curve when α=1: for other values of α each consumer's true value is the same, but the ordering of consumers along the value curve is different, since the demand curve reflects a different ordering of consumers.

As mentioned before, the construction of $V(P;\alpha)$ embeds the assumption that the estimated demand impacts of observed information frictions are not welfare-relevant once a consumer is actually allocated to a given plan. For some of the frictions we study (e.g. information about provider networks) this assumption seems very reasonable, while for others (e.g. perceived hassle costs) this is less clear. It is straightforward to alter the definition of V for different underlying models mapping revealed willingness-to-pay and measured frictions to welfare-relevant valuations.[52,53]

[52] If consumers don't know that the network of providers is the same in both plans, and this impacts their relative willingness to pay for the PPO as estimated, then this impact on willingness to pay should not be welfare-relevant conditional on enrollment, when consumers will in fact have the same providers (as long as ex ante information doesn't differentially impact search for providers ex post). The same logic applies to knowledge about plan financial characteristics (such as deductible and OOP max) and knowledge of own health expenditures though with each friction considered there may be different hypotheses about the link between ex ante information and ex post actions. With deductible and coinsurance and out-of-pocket maximum whether consumers take different ex post action based on their ex ante information depends on (i) whether knowledge of those features impacts ex post utilization and (ii) how consumers acquire knowledge about these plan features once enrolled.

[53] The analysis in Handel and Kolstad (2015b) reveals that the relative perceived difference in hassle costs between the PPO and $HDHP$ is substantially larger than the actual experienced difference between those two plans. However, it is also clear from the analysis that some of the perceived difference in hassle costs between the two plans are real. This suggests that *some* of the perceived relative difference in hassle costs is real, and some reflects a lack of information. As a result, for this friction, some should likely be counted as welfare-relevant conditional on enrollment, and some should not. Incorporating this into our framework would shift the value curve towards the demand curve in the environment with full information frictions. Our analysis here could thus also reflect the same counterfactual

The average and marginal cost curves relevant to the insurer are determined by the insurer costs and the insurer risk-adjustment transfers, but also depend on the underlying preferences and information frictions (due to the sorting effect). Empirically, total expected family spending is estimated in the cost model described in Section 4 and Online Appendix B. Define $c_{k,PPO}$ as total insurer costs for family k (including supplemental insurer costs and baseline insurer costs). Since this option provides 100% coverage, this is the same as total expected family spending. Define $c_{k,HDHP}$ as insurer costs for just the HDHP (i.e. the baseline plan). The difference between the two equals the supplemental insurer cost:

$$c_k = c_{k,PPO} - c_{k,HDHP}.$$

Given the full coverage provided by the PPO, this supplemental cost corresponds to the mean of family out-of-pocket spending in the HDHP. Risk-adjustment transfers compensate insurers for a share β of the difference in costs for the selection of families buying insurance and the average cost in the population. In the market for supplemental insurance the marginal cost curve is defined as follows for a given policy combination (α, β):

$$MC(P;\alpha,\beta) = E[c_k|w_k(\alpha) = P] - \beta E[c_k|w_k(\alpha) = P] - (AC_{pop,PPO} - AC_{pop,HDHP}),$$

where $\beta = 1$ denotes perfect risk-adjustment. This is the insurer MC curve given risk-adjustment: the true marginal cost curve, *which is the cost curve relevant for welfare analysis*, is defined as the insurer marginal cost curve where $\beta = 0$ (i.e., $MC(P;\alpha,0)$ for each P). The average cost curve $AC(P;\alpha,\beta)$ simply traces out the average of supplemental costs for those with willingness to pay greater than or equal to P:

$$AC(P;\alpha,\beta) = E[c_k|w_k(\alpha) \geq P] - \beta[E[c_k|w_k(\alpha) \geq P] - (AC_{pop,PPO} - AC_{pop,HDHP})]$$

The insurer cost curves depend on α because, as shown in Section 2 and the correlations in Section 4, as frictions are reduced, the sorting of individuals into insurance differs: costs become a more prominent driver of demand as frictions are reduced, so the correlation between costs and willingness to pay becomes higher, leading to different costs curves as a function of quantity demanded at a given relative price. The insurer cost curves also depend on β, the insurer risk-adjustment transfers, because as risk-adjustment transfers are implemented between insurers the contribution of a given consumer to plan cost is mitigated by transfers and the curves become flatter. Equilibrium in the market occurs at the lowest value of P such that $P = AC(P;\alpha,\beta)$, under a set of regularity conditions which we assume hold here. We also note here that, because there is only one type of non-horizontally differentiated priced plan, risk-adjustment implies a transfer into (or out of) this supplemental market if the market is adversely (advantageously) selected. This is a

environment, with the additional assumption that all real hassle cost differences between plans are removed.

feasible policy approach both in theory and practice (see the the discussion in e.g. Handel et al. (2015) or Mahoney and Weyl (2014) for greater detail). Finally, we note that for the alternative market setup where both coverage tiers are competitively offered, construction of the average and marginal costs curves is different than for the supplemental market described here. See Appendix D for a lengthier discussion.[54]

Once we have determined the equilibrium outcome in each market, we compute incremental consumer welfare from more generous coverage as the difference between a consumer's welfare-relevant valuation v_k and actual relative marginal cost c_k (for $\beta = 0$):

$$s_k = v_k - c_k$$

For a given equilibrium allocation and price P, the welfare loss relative to the first-best, where everyone enrolls in more comprehensive coverage (i.e., $s > 0$), is:

$$\Sigma_k s_k 1[w_k(\alpha) < P]$$

Using this metric, in the next section we compare the welfare impact of different friction-reducing and risk-adjustment policies, both relative to other candidate policies and relative to a first-best.

6 Empirical Results

In this section we present our main empirical results. We first evaluate the positive and normative implications of friction-reducing policies on their own, then discuss the impact of these policies conditional on different levels of risk-adjustment effectiveness. We focus on the Einav et al. (2010b) style market for supplemental coverage, which provides incremental coverage relative to the HDHP baseline plan. We present the empirical results for exchange-style markets with two priced plans in Appendix D. We present results only for the family coverage tier, who comprise the majority of our sample and form a natural population for a community rated market (since typically firms can vary premiums w/ number of enrollees). For all results, we present a version of our estimates that fits the non-parametric curves with splines: upon request we have completed and can provide a

[54]The relevant insurer cost curves are different for the Handel et al. (2015) style market where two classes of plans are priced. Now, the PPO insurers internalize the full costs of consumers enrolling, $c_{k,PPO}$, not just the supplemental costs $c_{k,PPO} - c_{k,HDHP}$. Additionally, the HDHP plan must now break-even in equilibrium, which is not the case when it is a publicly provided baseline plan. As shown in Handel et al. (2015), with a fully enforced mandate the difference in average costs between the two classes of priced plans must equal the difference in prices in a Nash or Riley equilibrium. Relative average costs in this market as a function of α and β are:

$$\begin{aligned}\Delta AC(\Delta P; \alpha, \beta) = \quad & E[c_{k,PPO}|w_k(\alpha) \geq \Delta P] - \beta(E[c_{k,PPO}|w_k(\alpha) \geq \Delta P] - AC_{pop,PPO}) \\ & -E[c_{k,HDHP}|w_k(\alpha) \leq \Delta P] - \beta(E[c_{k,HDHP}|w_k(\alpha) \leq \Delta P] - AC_{pop,HDHP})\end{aligned}$$

Handel et al. (2015) establishes a set of regularity conditions under which a Riley equilibrium exists and equals the lowest ΔP satisfying the condition $\Delta P = \Delta AC(\Delta P; \alpha, \beta)$. Riley equilibrium restricts the space of possible deviations for a candidate equilibrium relative to a Nash equilibrium (which sometimes will not exist in this type of environment). See Handel et al. (2015) for further details.

linearized version (as in Einav et al. (2010b), which is more restrictive, and a fully non-parametric version, which is less restrictive.

6.1 Information Frictions and Equilibrium

Information frictions impact both the number of individuals buying each type of plan and the sorting of individuals across plans. Therefore, we expect both the level and slope of the demand, cost, and value curves to change as α changes. Figures 14, 15 and 16 present these sets of curves graphically for full ($\alpha = 0$), half ($\alpha = .5$) and no ($\alpha = 1$) choice frictions. Recall that when $\beta = 0$ and there is no risk-adjustment, as in these figures, the true marginal cost curve for consumers is the same as the insurer marginal cost curve. Note also that the value and marginal cost curves correspond to the same ordering of individuals as the demand curve for each scenario.

Figure 14, which replicates the demand, value, and cost curves as estimated in our environment (with all frictions present), illustrates some key implications of our estimates. First, the frictions present in our environment drive a substantial wedge between the demand curve and welfare-relevant value curve: the demand curve lies well above the value curve, indicating that consumers on average over-value the more comprehensive PPO plan relative to the $HDHP$. This is true along the entire demand curve and thus even for consumers with a relatively low willingness to pay for the supplemental coverage. Second, it is clear from the charts that the surplus of the supplemental coverage is quite small, especially relative to the impact of frictions on willingness-to-pay. In each figure, surplus is represented by the wedge between the marginal cost curve and the welfare-relevant value curve and corresponds to the risk-premia consumers are willing to pay to be in the PPO as opposed to the $HDHP$, depending on their risk preferences and health risks. Estimated risk premia are fairly low due to both the low degree of estimated risk aversion (see Table 6) and the fact that downside risk in the $HDHP$ is limited by the out-of-pocket maximum (for families, this is between \$6,000-\$7,000). Finally, we note that while the average cost curve is downward sloping — a necessary condition for adverse selection — the slope is relatively flat. This indicates that, when full frictions are present, marginal enrollee costs to the PPO are not substantially different than those of infra-marginal enrollees and there is limited scope for adverse selection.

In the context of the simulations presented in Section 2.5, our empirical environment is one with high mean and variance of frictions, low mean and variance of surplus, and medium to high mean and variance in expected yearly costs. As a result, as we saw in that section, we expect that friction-reducing policies will lead to substantial unraveling in the absence of complementary risk-adjustment.

Table 8 presents the positive market equilibrium results associated with different policy combinations. The first column, for $\beta = 0$ gives the results for the cases of different friction-reducing policies when there is no insurer risk-adjustment (as shown in Figures 14-16). In all cases, since the value curve lies about the consumer marginal cost curve, 100% of consumers should be allocated to the PPO from a social perspective. In our conclusions, we return to these results and discuss

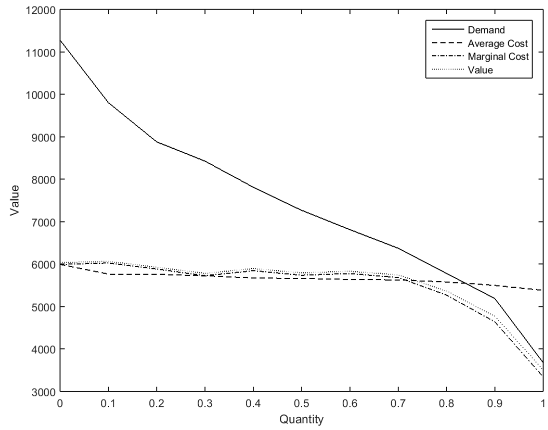

Figure 14: Market Equilibrium Including Information Frictions

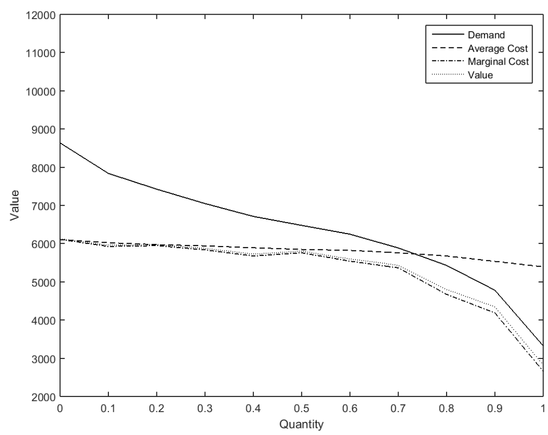

Figure 15: Market Equilibrium with Partial Information Frictions

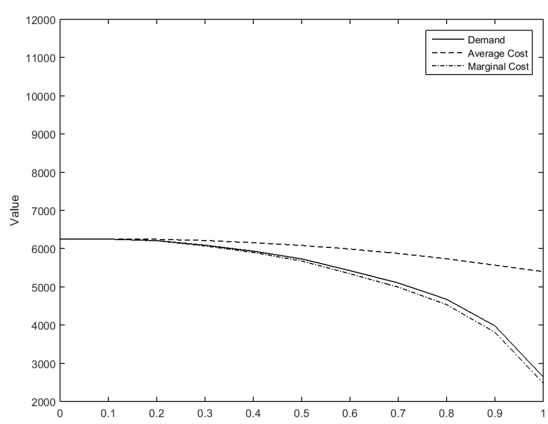

Figure 16: Market Equilibrium without Information Frictions

un-modeled factors that would change this first-best allocation, such as moral hazard.[55]

For the case of full frictions ($\alpha = 0$) the predicted market equilibrium outcome (the one crossing point between the demand and average cost curves) is 84.6% enrolled in the PPO and 15.4% enrolled in the $HDHP$. The price paid for supplemental coverage in equilibrium equals $P = \$5,551$. For the case of half frictions ($\alpha = 0.5$, Figure 15), 73.4% buy the PPO and 26.6% buy the $HDHP$ in equilibrium, with a relative premium difference of $P = \$5,741$. Thus, when the impact of frictions are reduced by 50% there is only limited incremental adverse selection against the PPO, with market share declining and the relative premium rising.

When all frictions are removed ($\alpha = 1$, Figure 16) the demand curve and value curve are equivalent, with demand shifting downward relative to the case where frictions are present. In addition, the marginal and average cost curves become steeper reflecting the sorting effect as consumer marginal costs are much more highly correlated with consumer demand. Now, the market equilibrium reflects an almost complete unraveling of the market due to adverse selection: 9.1% of consumers buy the PPO, 90.9% buy the $HDHP$ and the relative premium is $P = \$6,250$.

Both the level and sorting effects lead to the unraveling of the market as information frictions are reduced in our environment. The level effect can be seen clearly in Figures 14-16 above, as the demand shifts down substantially as frictions are reduced (also for the marginal consumers). The sorting effect can be seen clearly in Figure 17: as frictions are reduced the average cost curve becomes steeper, implying that the correlation between consumer costs and demand is increasing. Table 7 shows that this correlation increases from 0.508 to 0.999 as frictions are reduced to non-existant. In essence, the presence of information frictions drives a gap between demand and welfare-relevant valuation, and the correlation of those frictions with costs determines if removing frictions has a marked sorting effect. In our case, frictions are not particularly highly correlated with costs, so when they are present they have a substantial impact on the ordering of willingness-to-pay for more insurance.

The bottom portion of Table 8 presents the welfare implications of friction-reducing policies. In our environment, where consumers benefit from more risk protection (assuming no corresponding efficiency loss from increased moral hazard), welfare is generally decreasing as the market unravels and enrollment in the more generous PPO plan goes down (this is not necessarily true because of the improved matching as discussed before). Our welfare results show that, relative to the status quo environment, when frictions are reduced by 50% consumers are worse off by an average of \$16.04 (35% of mean total surplus) per person. When frictions are fully removed and the market unravels, consumers are on average \$47.01 (99% of mean total surplus) worse off per person. This is a meaningful drop in welfare for a policy that most policymakers would expect to only have positive consequences. One way to counter these welfare losses are risk-adjustment transfer policies; interactions between those policies and reduced frictions is discussed next.

[55]Note that in the linear versions of our analysis, shown in Appendix E, the graphs illustrate that the first-best allocation has less than 100% of consumers enrolled in the PPO (at the point where the value curve intersects the consumer marginal cost curve). This reflects the fact then when all curves are linearized, some of the key implications of the micro-foundations of a more flexible model are not faithfully represented. The analysis in that appendix highlights the differing results between the linear case and our main case presented here.

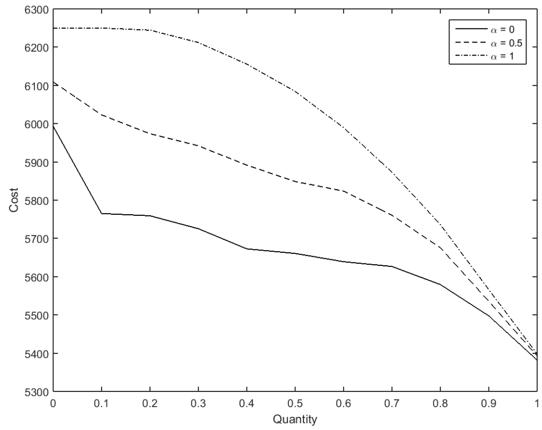

Figure 17: Average Cost Curves with Varying Levels of Information Frictions.

Positive Policy Impacts

	$\beta = 0$	$\beta = .2$	$\beta = .5$	$\beta = .8$	$\beta = 1$
Quantity PPO					
$\alpha = 0$	84.6%	85.5%	87.1%	88.0%	88.5%
$\alpha = .2$	81.9%	83.3%	84.6%	85.7%	86.4%
$\alpha = .5$	73.7%	76.1%	78.6%	80.9%	82.0%
$\alpha = .8$	51.7%	59.4%	68.0%	72.0%	74.1%
$\alpha = 1$	9.1%	34.7%	51.6%	59.0%	63.5%
Price of Supplemental Coverage P					
$\alpha = 0$	\$5,551	\$5,498	\$5,425	\$5,358	\$5,315
$\alpha = .2$	\$5,611	\$5,544	\$5,452	\$5,368	\$5,315
$\alpha = .5$	\$5,741	\$5,643	\$5,507	\$5,385	\$5,315
$\alpha = .8$	\$6,035	\$5,835	\$5,596	\$5,418	\$5,315
$\alpha = 1$	\$6,250	\$6,014	\$5,694	\$5,452	\$5,315

Welfare Impact*

	$\beta = 0$	$\beta = .2$	$\beta = .5$	$\beta = .8$	$\beta = 1$
$\alpha = 0$	0	0.97	2.34	3.30	4.30
$\alpha = 0.2$	-4.96	-3.44	-1.98	-0.58	0.40
$\alpha = 0.5$	-16.04	-13.92	-11.15	-7.97	-6.36
$\alpha = 0.8$	-36.63	-31.29	-24.21	-20.23	-17.95
$\alpha = 1$	-47.01	-45.13	-38.30	-33.15	-29.34

*Relative to $(\alpha = 0, \beta = 0)$

Table 8: The first two sections of this table present the market outcomes in prices and quantities for different policy combinations of (i) friction-reducing policies and (ii) insurer risk-adjustment transfers. The third panel presents the relative welfare impact of different policies; policies are compared to information frictions and zero risk adjustment ($\alpha = 0$ and $\beta = 0$).

6.2 Risk Adjustment and Equilibrium

It is clear that information frictions can have important implications for equilibrium insurance choices as well as the degree of adverse selection in a market. As shown, policies that mitigate information frictions (e.g. personal decision tools) could have a marked, and not necessarily positive, impact on market outcomes if they are effective. Insurer risk-adjustment transfer are an oft-discussed and oft-implemented policy tool designed to specifically mitigate adverse selection in insurance markets with community rating.[56] In this section, we examine the implications of insurer risk-adjustment policies, parametrized by β as described in Sections 2 and 5.

We demonstrate the impact of risk-adjustment policies spanning $\beta = 0$ to $\beta = 1$ in this section conditional on $\alpha = 1$, or when frictions are already fully removed. Figure 18 presents the demand curve for $\alpha = 1$ (equivalent to the value curve) and three average cost curves, corresponding to the cases of $\beta = 0$, $\beta = 0.5$, and $\beta = 1$. From the figure, it is clear that as risk-adjustment becomes stronger, the average cost curve becomes flatter, becoming completely flat when $\beta = 1$ and all consumers have the same cost from the insurer's perspective. It is clear that as risk-adjustment becomes more effective, the market share of the PPO plans increase, and the market equilibrium moves towards the first-best of 100% PPO enrollment. Table 8 presents the resulting market shares and premiums: for the cases of $\beta = 0$, $\beta = 0.5$, and $\beta = 1$ the resulting market shares when $\alpha = 0$ are 9.1%, 51.6%, and 63.5% respectively. The relative premiums between the two tiers of plans are \$6,250, \$5,964, and \$5,315 respectively. Thus, conditional on frictions being fully removed, risk-adjustment has a substantial impact of reducing premiums in the PPO relative to the $HDHP$, and increasing market share in the PPO. Also welfare in the market is increasing as insurer risk-adjustment policies become more effective: when frictions are fully removed, risk-adjustment that is 50% effective increases welfare by \$8.71 (19% of mean total surplus) per person on average. When risk-adjustment is 100% effective, welfare increases by \$17.67 (39% of mean total surplus) per person on average.

Figure 19 presents the same curves for these three risk-adjustment policies, for the case of $\alpha = 0$ (our observed environment). Here, though the directional impacts of stronger risk-adjustment on plan market shares and relative premiums are the same as when $\alpha = 1$, the incremental effect is much weaker because the frictions present in the environment already reduce adverse selection to a large extent. The quantity in the PPO increases from 84.2% to 88.5% as β goes from 0 to 1, with the relative price decreasing from $5,551$ to $5,315$. The corresponding impact on welfare is again positive, but small. Welfare increases by \$4.30 (9% of mean total surplus) per person on average.

Comparing the case without and with frictions (Figures 18 and 19), we find that the impact of risk-adjustment policies is very different. In the next subsection, we discuss the interactions between choice-enhancing and insurer risk-adjustment policies in more depth.

[56]See e.g. Glazer et al. (2014) for an extended discussion of the economics of insurer risk-adjustment as implemented in a variety of contexts. See e.g., Mahoney and Weyl (2014) or Handel et al. (2015) for further discussion of market equilibria with risk-adjustment.

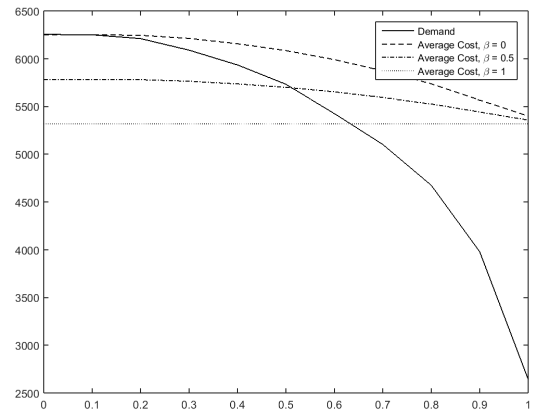

Figure 18: Market Equilibrium with three levels of β, for $\alpha = 1$

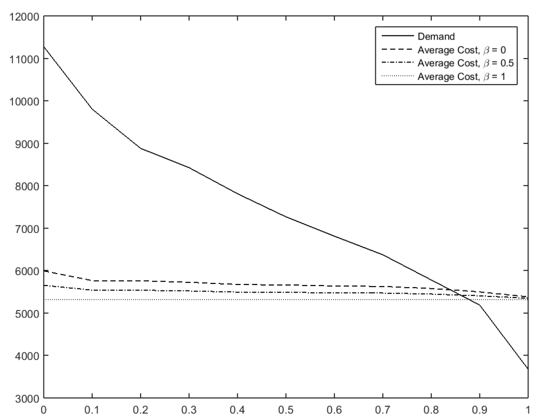

Figure 19: Market Equilibrium with three levels of β, for $\alpha = 0$

6.3 Policy Interactions

The marginal impact of either (i) friction-reducing policies or (ii) insurer risk-adjustment transfers depends crucially on the effectiveness of the other policy within any given environment. One important implication of this is that policymakers considering policies to improve consumer decisions may want to simultaneously strengthen insurer risk-adjustment policies in order to prevent incremental adverse selection. As shown in Section 2.5, this is especially true in cases like our empirical environment, where the mean and variance of surplus are low relative to the mean and variance of costs.

Figures 20-22 plot market equilibrium quantities, prices, and welfare outcomes for all combinations of policies $\alpha \in [0, 1] \times \beta \in [0, 1]$. Select numbers from these three charts are reported in Table 8. The key insight across all three figures is that effective risk-adjustment becomes increasingly impactful and important as information frictions are reduced. For low to medium values of α, where substantial choice frictions are still present, more effective risk-adjustment has only a minimal impact on market outcomes and welfare. This is because the average cost curve is already quite flat for low values of α, so there is not much scope for risk-adjustment to further change market outcomes by resorting consumers and further flattening the cost curve. However, for high values of α, where the cost curves are steeper and preferences have been shifted towards the $HDHP$ via the level effect, risk-adjustment has an immediate and strong effect by flattening the cost curve, reducing adverse selection and improving market outcomes. Simply put, if consumer choices are less responsive to a consumer's specific cost, decoupling insurer pricing from individual specific risk has less of an impact.

Figure 22 and the bottom panel of Table 8 show the welfare impact of possible policy combinations in the $\alpha - \beta$ space. Risk-adjustment policies have a large incremental impact when friction-reducing policies are very effective: when $\alpha = 1$ moving β from 0 to 1 improves welfare by \$17.67 per person on average, while when $\alpha = 0$ the same movement in β improves welfare by \$4.30 per person on average. For $\alpha = 0.2$, $\beta = 1$ still leads to a welfare improvement relative to the status quo, while for values $\alpha = 0.5$ and above no degree of risk-adjustment improves welfare relative to the baseline case.

This empirical analysis reflects the case where there is low mean consumer surplus from incremental insurance and low surplus variance, relative to the degree of frictions in the market and the variance in projected costs. As a result, as frictions are removed, the market unravels relatively quickly because costs feed back into premiums but lower cost consumers don't have high enough true surplus to justify the purchase of incremental insurance when frictions are reduced. In different insurance environments, the mean and variance of surplus may be larger (e.g. if there is no out-of-pocket maximum or consumers are more risk averse than those here) which, as our simulations in Section 2 reveal, may lead frictions reducing policies to have positive impacts on their own. In such cases, friction-reducing policies can and should be implemented even if effective risk-adjustment is not available.

7 Conclusion

In this paper we set up a framework to study insurance market equilibrium and the welfare that results for environments where consumers have limited information. When limited information impacts consumer plan choices, understanding the relationship between key micro-foundations such as (i) surplus from risk protection (ii) the impact of frictions on willingness-to-pay and (iii) consumer/insurer costs is important for making policy decisions. We use this framework to investigate demand-side policies that reduce consumer information frictions, thereby helping consumers make better plan choices, and insurer risk-adjustment transfers, a supply-side policy designed to mitigate adverse selection by dampening the relationship between consumer costs and insurer costs.

We provide simple expressions and simulations showing that when frictions distort consumers plan choices (to different degrees and in potentially different directions) the mean and variance of the distribution of surplus, relative to those of costs, are crucial for assessing whether friction-reducing policies will improve welfare. In cases where the distribution of surplus is low relative to that of costs, friction-reducing policies lower demand and increase adverse selection, reducing

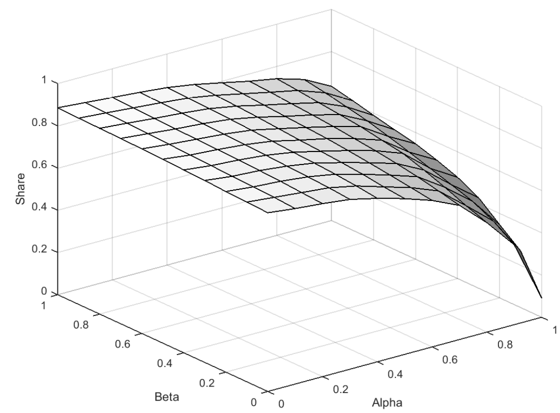

Figure 20: Market equilibrium PPO market shares for ranges of policies for α and β between 0 and 1, with full interactions.

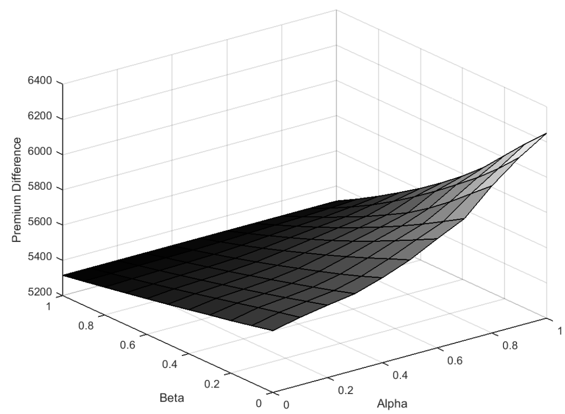

Figure 21: Market equilibrium δP for ranges of policies for α and β between 0 and 1, with full interactions.

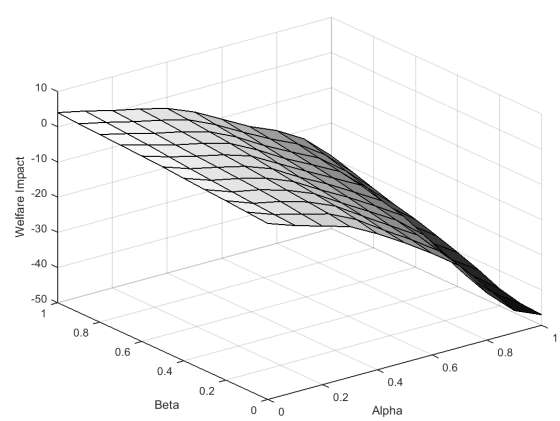

Figure 22: Market equilibrium welfare outcomes for ranges of policies for α and β between 0 and 1, with full interactions.

equilibrium coverage and welfare. In cases where the distribution of surplus is high relative to that of costs, friction-reducing policies may increase demand and the match of consumers to plans based on surplus increasing welfare. The supply-side policy of risk-adjustment transfers flattens the relationship between insurer costs and consumer willingness-to-pay for insurance. In doing so, as risk-adjustment policies become more effective friction-reducing policies are more likely to be welfare increasing, making these two sets of policies complementary. Conversely, as the market foundations make incremental adverse selection from reduced frictions more likely, more effective risk-adjustment policies are essential before friction-reducing policies are implemented, even when choice frictions are substantial.

We take these insights from the model and apply them to an empirical setting of a large self-insured employer, where prior work by Handel and Kolstad (2015b) provides structural estimates of (i) costs (ii) risk preferences and (iii) the impact of frictions on willingness-to-pay. We use these estimates to construct demand, cost, and value curves for a counterfactual market where insurers compete to offer supplemental insurance relative to a baseline plan, in the spirit of previous work by Einav et al. (2010b). After establishing that information frictions have a substantial impact increasing demand for generous coverage, we investigate the implications of a policy that reduces the impact of information frictions (e.g. through information provision). We find that a policy that reduces the impact of information frictions by 50% reduces the market share of consumers enrolling in more generous coverage from 85% to 73%, and that a policy that fully removes information friction further reduces the market share in generous coverage to 9% (with corresponding welfare reductions). We illustrate that this negative impact of reducing frictions occurs because the mean and variance of surplus are low relative to the mean and variance of costs. We also show that as friction-reducing policies become stronger, effective insurer risk-adjustment transfers are more important. When frictions are fully present, fully effective risk-adjustment increases the market share in generous insurance from 85% to 88%, but when there are no frictions that same risk adjustment policy increases this share from 9% to 64% (with corresponding welfare increases).

Our results reflect one specific setting. However, they highlight the subtleties that determine when policies to reduce consumer frictions will be welfare increasing or welfare decreasing. Crucially, the impact of these policies depends not only on the distributions of other micro-foundations in the market, but also on how effective complementary supply-side policies, such as insurer risk-adjustment transfers are. If insurer risk-adjustment policies are not shown to be highly effective (see e.g. Brown et al. (2014)) then policymakers may want to be more conservative in implementing policies that heavily reduce the impact of information frictions in the market. This is especially true in cases where the mean and variance of costs are high relative to those of consumer surplus. These insights are important for policymakers thinking about implementing policies such as information provision, plan recommendations, and smart defaults all of which are being currently considered by different insurance market regulators.

It is crucial to note that our empirical example is intended to illustrate how our framework can be directly taken to data. The underlying micro-foundations we measure are likely to be different than those in other markets and the corresponding conclusions about policy will change as described in Section 2. For example, a range of papers show meaningful consumer choice frictions in Medicare Part D (see for example Abaluck and Gruber (2011) or Ketcham et al. (2012)), where the mean and variance of costs is lower than in our market (because it insurers only prescription drugs) and risk-adjustment may be very effective (because of the predictability of drug use). In that case, our framework suggests that friction-reducing policies are more likely to be welfare improving than in the empirical environment we investigate in this paper. Of course, the relevant micro-foundations must be measured in each context to directly apply our framework, though our results demonstrate methods to do so as well as the feasibility.

Finally, we note that our framework contains a range of stylized assumptions that could impact the conclusions in any given context. First, we assume perfect competition. As Mahoney and Weyl (2014) show, imperfect competition can have subtle implications for policy recommendations in selection markets. However, the relevant micro-foundations to apply our framework remain the same. Second, our approach maintains quite stylized assumptions about the potentially endogenous relationship between the extent of competition in the market and consumer information. It is possible that the extent of limited information in any given setting is partially related to the degree of competition and/or the extent of risk-adjustment policies, an area that we believe is an interesting topic for future work. Third, we abstracted away from consumer moral hazard, to clearly focus on the other micro-foundations in the market. Though the relationships we explore would generally be robust to including moral hazard in the model, the mean and variance of that price sensitivity could have important implications for whether increasing coverage is a desirable social goal. We believe that extending our analysis by relaxing these assumptions is an interesting avenue for future work. Fourth, we focus on the case where frictions push consumers towards more generous coverage: this example is relevant in practice, and much of the intuition of our framework can be applied to that case, in reverse, where relevant in future work.

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A Appendix: Proofs

Proof of Proposition 1: *We consider a budget-balanced policy x that maintains the ordering of individuals' willingness-to-pay and thus the corresponding surplus from buying insurance conditional on the share of insured individuals. We denote by $\tilde{w}_i(x)$ individual i's net willingness-to-pay and the corresponding density by $g^{\tilde{w}(x)}$. Equilibrium welfare for policy x (not accounting for the budgetary cost) equals*

$$\begin{aligned} \mathcal{W}(x) &= \int_{D^{-1}(Q(x);x)} E_{\tilde{w}'}(s)\, g^{\tilde{w}(x)}\left(\tilde{w}'\right) d\tilde{w}', \\ &= \int_{D^{-1}(Q(x);0)} E_{w'}(s)\, g\left(w'\right) dw'. \end{aligned}$$

The second equality follows by maintaining the ordering for any intensity of the policy x. The welfare effect of an increase in x only goes through the equilibrium quantity,

$$\mathcal{W}'(x) = \frac{\partial}{\partial Q}\left[\int_{D^{-1}(Q(x);x)}^{\infty} E_{\tilde{w}'}(s)\, g^{\tilde{w}(x)}\left(\tilde{w}'\right) d\tilde{w}'\right] Q'(x).$$

Using Leibniz' rule and $\frac{\partial}{\partial Q}D^{-1} = \frac{-1}{g^{\tilde{w}(x)}}$, we find

$$\begin{aligned} \mathcal{W}'(x) &= -E_{P(x)}(s)\, g^{\tilde{w}(x)}(P)\frac{\partial}{\partial Q}D^{-1}(Q(x);x)\, Q'(x) \\ &= E_{P(x)}(s)\, Q'(x) = \left[P(x) - E_{P(x)}(c) - E_{P(x)}(f)\right] Q'(x). \end{aligned}$$

Hence, a policy that increases Q, ceteris paribus, increases welfare if and only if $P - E_P(c) \geq E_P(f)$.□

Proof of Proposition 2: *The equilibrium is characterized by $P^c(\alpha) = E_{\geq P^c(\alpha)}(c)$ where $P^c(\alpha) = D^{-1}(Q^c(\alpha);\alpha)$. We can solve for the change in coverage by implicit differentiation. The main challenge is to derive how the conditional expectation $E_{\geq P^c}(c)$ changes.*
We first consider a change in the equilibrium price. Note that

$$E_{\geq P^c}(c) = \frac{1}{1 - G^{\tilde{w}(\alpha)}(P^c)}\int_{P^c}^{\infty} E_{\tilde{w}(\alpha)=\tilde{w}'}(c)\, g^{\tilde{w}(\alpha)}\left(\tilde{w}'\right) d\tilde{w}',$$

where we denote individual i's net willingness-to-pay by $\tilde{w}_i(\alpha)$ and the corresponding density by $g^{\tilde{w}(\alpha)}$. Using Leibniz' rule, we find

$$\frac{\partial}{\partial P}\left[\int_{P^c} E_{\tilde{w}(\alpha)=\tilde{w}'}(c)\, g^{\tilde{w}(\alpha)}\left(\tilde{w}'\right) d\tilde{w}'\right] = -E_{\tilde{w}(\alpha)=P^c}(c)\, g^{\tilde{w}(\alpha)}(P^c).$$

Hence, using $\partial\left[1 - G^{\tilde{w}(\alpha)}(P)\right]/\partial P = -g^{\tilde{w}(\alpha)}(P)$, we find

$$\frac{\partial}{\partial P}E_{\geq P^c}(c) = \left[E_{\geq P^c}(c) - E_{P^c}(c)\right]\frac{g^{\tilde{w}(\alpha)}(P^c)}{1 - G^{\tilde{w}(\alpha)}(P^c)},$$

which depends on the difference between average and marginal cost.
Evaluating the impact of the information policy on $E_{\geq P^c}(c)$ is more difficult, since it interacts with

individuals' friction value. However, using the law of iterated expectations, we can re-write

$$\begin{aligned}
&\int_{P^c} E_{\tilde{w}(\alpha)=\tilde{w}'}(c)\, g^{\tilde{w}(\alpha)}\left(\tilde{w}'\right) d\tilde{w}' \\
&= \int\int_{P^c} E\left(c|\tilde{w}(\alpha)=\tilde{w}', f=f'\right) g^{\tilde{w}(\alpha)|f}\left(\tilde{w}'|f'\right) d\tilde{w}' g^f\left(f'\right) df' \\
&= \int\int_{P^c} E\left(c|w=\tilde{w}'+\alpha f', f=f'\right) g^{w|f}\left(\tilde{w}'+\alpha f'|f'\right) d\tilde{w}' g^f\left(f'\right) df' \\
&= \int\int_{P^c+\alpha f'} E\left(c|w=w', f=f'\right) g^{w|f}\left(w'|f'\right) dw' g^f\left(f'\right) df'.
\end{aligned}$$

The last equality uses the substitution $w'=\tilde{w}'+\alpha f'$ and thus $dw'=d\tilde{w}'$. Now we can write

$$\begin{aligned}
&\frac{\partial}{\partial\alpha}\left[\int_{P^c} E_{\tilde{w}(\alpha)=\tilde{w}'}(c)\, g^{\tilde{w}(\alpha)}\left(\tilde{w}'\right) d\tilde{w}'\right] \\
= \quad & \int \frac{\partial}{\partial\alpha}\left[\int_{P^c+\alpha f} E\left(c|w=w', f=f'\right) g^{w|f}\left(w'|f'\right) dw'\right] g^f\left(f'\right) df' \\
= \quad & -\int\left[E\left(c|w=P^c+\alpha f', f=f'\right) g^{w|f}\left(P^c+\alpha f'|f'\right)\times f'\right] g^f\left(f'\right) df' \\
= \quad & -\int\left[E\left(c\times f|w=P^c+\alpha f', f=f'\right) g^{w|f}\left(P^c+\alpha f'|f'\right)\right] g^f\left(f'\right) df'.
\end{aligned}$$

Using again the law of iterated expectations and the reverse subsitution, we find

$$\frac{\partial}{\partial\alpha}\left[\int_{P^c} E_{\tilde{w}(\alpha)=\tilde{w}'}(c)\, g^{\tilde{w}(\alpha)}\left(\tilde{w}'\right) d\tilde{w}'\right] = -E_{P^c}(c\times f)\, g^{\tilde{w}(\alpha)}\left(P^c\right).$$

In an analogue way, we can find

$$\frac{\partial}{\partial\alpha}\left[\int_{P^c} g^{\tilde{w}(\alpha)}\left(w'\right) dw'\right] = -E_{P^c}(f)\, g^{\tilde{w}(\alpha)}\left(P^c\right).$$

Hence,

$$\begin{aligned}
\frac{\partial}{\partial\alpha} E_{\geq P^c}(c) &= \left[E_{\geq P^c}(c)\, E_{\tilde{w}(\alpha)}(f) - E_{P^c}(c\times f)\right] \frac{g^{\tilde{w}(\alpha)}\left(P^c\right)}{1-G^{\tilde{w}(\alpha)}\left(P^c\right)} \\
&= \left[\left(E_{\geq P^c}(c) - E_{P^c}(c)\right) E_{\tilde{w}(\alpha)}(f) - cov_{P^c}(c,f)\right] \frac{g^{\tilde{w}(\alpha)}\left(P^c\right)}{1-G^{\tilde{w}(\alpha)}\left(P^c\right)},
\end{aligned}$$

which depends on the difference between average and marginal costs as well.

By implicit differentiation of the equilibrium condition $D^{-1}\left(Q^c(\alpha);\alpha\right) = E_{\geq D^{-1}(Q^c(\alpha);\alpha)}(c)$, we find

$$Q^{c\prime}(\alpha) = -\frac{\left[1-\frac{\partial}{\partial P^c}E_{\geq P^c}(c)\right]\frac{\partial D^{-1}(Q^c;\alpha)}{\partial\alpha} - \frac{\partial}{\partial\alpha}E_{\geq P^c}(c)}{\left[1-\frac{\partial}{\partial P^c}E_{\geq P^c}(c)\right]\frac{\partial D^{-1}(Q^c;\alpha)}{\partial Q}}.$$

with $\frac{\partial D^{-1}(Q^c;\alpha)}{\partial Q} = \frac{1}{-g^{\tilde{w}(\alpha)}(P^c)}$ and $\frac{\partial D^{-1}(Q^c;\alpha)}{\partial\alpha} = -E_{P^c}(f)$. Putting things together, the terms with

$[E_{\geq P^c}(c) - E_{P^c}(c)]$ drop out of the numerator and we find

$$Q^{c\prime}(\alpha) = -\frac{E_{P^c}(f) - cov_{P^c}(c,f)\frac{|\varepsilon_D(P^c)|}{P^c}}{1 - [E_{\geq P^c}(c) - E_{P^c}(c)]\frac{|\varepsilon_D(P^c)|}{P^c}} g^{\tilde{w}(\alpha)}(P^c),$$

using $\frac{g^{\tilde{w}(\alpha)}(P^c)}{1-G^{\tilde{w}(\alpha)}(P^c)} = \frac{|\varepsilon_D(P^c)|}{P^c}$. Notice that for a uniform subsidy S such that $P^c = E_{\geq P^c}(c) + S$, we have

$$Q^{c\prime}(S) = \frac{1}{1 - [E_{\geq P^c}(c) - E_{P^c}(c)]\frac{|\varepsilon_D(P^c)|}{P^c}} g^{\tilde{w}(\alpha)}(P^c) \equiv \eta^c.$$

Hence, the Proposition follows.$\square$

Proof of Proposition 3: *Consider the equilibrium price $P(\alpha)$ and quantity $Q(\alpha)$.* W*elfare equals*

$$\mathcal{W}(\alpha) = \int_{P(\alpha)} E_{\tilde{w}(\alpha)=\tilde{w}'}(s)\, g^{\tilde{w}(\alpha)}\left(\tilde{w}'\right) d\tilde{w}',$$

where $P(\alpha) = D^{-1}(Q(\alpha), \alpha)$. *The total impact of the policy on welfare depends on the policy's effect on the equilibrium quantity and its direct effect on welfare,*

$$\mathcal{W}'(\alpha) = \frac{\partial \mathcal{W}}{\partial P}\frac{\partial D^{-1}(Q(\alpha), \alpha)}{\partial Q} Q'(\alpha) + \frac{\partial \mathcal{W}}{\partial P}\frac{\partial D^{-1}(Q(\alpha), \alpha)}{\partial \alpha} + \frac{\partial \mathcal{W}}{\partial \alpha}.$$

By analogy to the proof of Proposition 2, we find

$$\begin{aligned}\frac{\partial \mathcal{W}}{\partial P} &= -E_{P(\alpha)}(s)\, g^{\tilde{w}(\alpha)}(P(\alpha)) \\ \frac{\partial \mathcal{W}}{\partial \alpha} &= -E_{P(\alpha)}(s \times f)\, g^{\tilde{w}(\alpha)}(P(\alpha)).\end{aligned}$$

Using $\frac{\partial D^{-1}(Q(\alpha);\alpha)}{\partial Q} = \frac{1}{-g^{\tilde{w}(\alpha)}(P(\alpha))}$ and $\frac{\partial D^{-1}(Q(\alpha);\alpha)}{\partial \alpha} = -E_{P(\alpha)}(f)$, we find

$$\begin{aligned}\mathcal{W}'(\alpha) &= E_{P(\alpha)}(s)\, Q'(\alpha) + E_{P(\alpha)}(s)\, E_{P(\alpha)}(f)\, g^{\tilde{w}(\alpha)}(P(\alpha)) - E_{P(\alpha)}(s \times f)\, g^{\tilde{w}(\alpha)}(P(\alpha)) \\ &= E_{P(\alpha)}(s)\, Q'(\alpha) - cov_{P(\alpha)}(s,f)\, g^{\tilde{w}(\alpha)}(P(\alpha))\end{aligned}$$

and the proposition immediately follows.$\square$

Proof of Proposition 4 *For a risk-adjustment policy β the competitive equilibrium is determined by*

$$P^c(\beta) = E_{\geq P^c(\beta)}(\tilde{c}(\beta))$$

and $Q^c(\beta) = D^{-1}(P^c(\beta))$. By implicit differentiation, we find

$$Q^{c\prime}(\beta) = -\frac{-\frac{\partial}{\partial \beta} E_{\geq P^c}(\tilde{c}(\beta))}{\left[1 - \frac{\partial}{\partial P^c} E_{\geq P^c}(\tilde{c}(\beta))\right]\frac{\partial D^{-1}(Q^c;\beta)}{\partial Q}}.$$

Like in the proof of Proposition 1, we find $\frac{\partial D^{-1}(Q^c;\beta)}{\partial Q} = \frac{1}{-g(P^c)}$ and

$$\frac{\partial}{\partial P^c} E_{\geq P^c}(\tilde{c}(\beta)) = [E_{\geq P^c}(\tilde{c}(\beta)) - E_{P^c}(\tilde{c}(\beta))]\frac{g(P^c)}{1 - G(P^c)}.$$

Moreover,

$$\begin{aligned}\frac{\partial}{\partial\beta}E_{\geq P^c}\left(\tilde{c}\left(\beta\right)\right) &= \frac{\partial}{\partial\beta}\left[\frac{1}{1-G\left(P^c\right)}\int_{P^c}^{\infty}E_{w'}\left(\tilde{c}\left(\beta\right)\right)g\left(w'\right)dw'\right]\\ &= \frac{1}{1-G\left(P^c\right)}\int_{P^c}^{\infty}E_{w'}\left(-\left[c-Ec\right]\right)g\left(w'\right)dw'\\ &= E_{\geq P^c}\left(c\right)-Ec\end{aligned}$$

Hence,

$$\begin{aligned}Q^{c\prime}\left(\beta\right) &= \frac{E_{\geq P^c}\left(c\right)-Ec}{1-\left[E_{\geq P^c}\left(c\right)-E_{P^c}\left(c\right)\right]\frac{\left|\varepsilon_D\left(P^c\right)\right|}{P^c}}g\left(P^c\right)\\ &= \eta^c\times\left[E_{\geq P^c}\left(c\right)-Ec\right],\end{aligned}$$

where η^c *equals the equilibrium impact of a uniform subsidy.*

Welfare equals

$$\mathcal{W}\left(\beta\right)=\int_{D^{-1}\left(Q^c\left(\beta\right)\right)}E_w\left(s\right)g\left(w'\right)dw'.$$

Hence,

$$\mathcal{W}'\left(\beta\right)=-E_{P^c}\left(s\right)\frac{1}{-g\left(P^c\right)}g\left(P^c\right)Q^{c\prime}\left(\beta\right).$$

This proves the second expression of the Proposition.□

B Appendix: Cost Model Setup and Estimation

This appendix describes the details of the cost model, which is summarized at a high-level in section 4.[57] The output of this model, F_{kjt}, is a family-plan-time specific distribution of predicted out-of-pocket expenditures for the upcoming year. This distribution is an important input into the choice model, where it enters as a family's predictions of its out-of-pocket expenses at the time of plan choice, for each plan option.[58] We predict this distribution in a sophisticated manner that incorporates (i) past diagnostic information (ICD-9 codes) (ii) the Johns Hopkins ACG predictive medical software package (iii) a non-parametric model linking modeled health risk to total medical expenditures using observed cost data and (iv) a detailed division of medical claims and health plan characteristics to precisely map total medical expenditures to out-of-pocket expenses.The level of precision we gain from the cost model leads to more credible estimates of the choice parameters of primary interest (e.g. risk preferences and information friction impacts).

In order to most precisely predict expenses, we categorize the universe of total medical claims into four mutually exclusive and exhaustive subdivisions of claims using the claims data. These categories are (i) hospital and physician (ii) pharmacy (iii) mental health and (iv) physician office visit. We divide claims into these four specific categories so that we can accurately characterize the plan-specific mappings from total claims to out-of-pocket expenditures since each of these categories maps to out-of-pocket expenditures in a different manner. We denote this four dimensional vector of claims C_{it} and any given element of that vector $C_{d,it}$ where $d \in D$ represents one of the four categories and i denotes an individual (employee or dependent). After describing how we predict this vector of claims for a given individual, we return to the question of how we determine out-of-pocket expenditures in plan j given C_{it}.

Denote an individual's past year of medical diagnoses and payments by ξ_{it} and the demographics age and sex by ζ_{it}. We use the ACG software mapping, denoted A, to map these characteristics into a predicted mean level of health expenditures for the upcoming year, denoted θ:

$$A : \xi \times \zeta \rightarrow \theta$$

In addition to forecasting a mean level of total expenditures, the software has an application that predicts future mean pharmacy expenditures. This mapping is analogous to A and outputs a prediction λ for future pharmacy expenses.

We use the predictions θ and λ to categorize similar groups of individuals across each of four claims categories in vector in C_{it}. Then for each group of individuals in each claims category, we use the actual ex post realized claims for that group to estimate the ex ante distribution for each individual under the assumption that this distribution is identical for all individuals within the cell. Individuals are categorized into cells based on different metrics for each of the four elements of C:

$$\begin{aligned} \text{Pharmacy:} \quad & \lambda_{it} \\ \text{Hospital / Physician (Non-OV):} \quad & \theta_{it} \\ \text{Physician Office Visit:} \quad & \theta_{it} \\ \text{Mental Health:} \quad & C_{MH,i,t-1} \end{aligned}$$

For pharmacy claims, individuals are grouped into cells based on the predicted future mean phar-

[57] The model is similar to that used in Handel (2013).

[58] In the consumer choice model, this is mostly useful for estimating out-of-pocket expenditures in the HDHP, since the PPO plan has essentially zero expenditures.

macy claims measure output by the ACG software, λ_{it}. For the categories of hospital / physician (non office visit) and physician office visit claims individuals are grouped based on their mean predicted total future health expenses, θ_{it}. Finally, for mental health claims, individuals are grouped into categories based on their mental health claims from the previous year, $C_{MH,i,t-1}$ since (i) mental health claims are very persistent over time in the data and (ii) mental health claims are uncorrelated with other health expenditures in the data. For each category we group individuals into a number of cells between 8 and 12, taking into account the trade off between cell size and precision.

Denote an arbitrary cell within a given category d by z. Denote the population in a given category-cell combination (d, z) by I_{dz}. Denote the empirical distribution of ex-post claims in this category for this population $\hat{G_{I_{dz}}}(\cdot)$. Then we assume that each individual in this cell has a distribution equal to a continuous fit of $\hat{G_{I_{dz}}}(\cdot)$, which we denote G_{dz}:

$$\varpi : \hat{G_{I_{dz}}}(\cdot) \rightarrow G_{dz}$$

We model this distribution continuously in order to easily incorporate correlations across d. Otherwise, it would be appropriate to use $G_{I_{dz}}$ as the distribution for each cell.

The above process generates a distribution of claims for each d and z but does not model correlations over D. It is important to model correlation over claim categories because it is likely that someone with a bad expenditure shock in one category (e.g. hospital) will have high expenses in another area (e.g. pharmacy). We model correlation at the individual level by combining marginal distributions G_{idt} $\forall$ d with empirical data on the rank correlations between pairs (d, d').[59] Here, G_{idt} is the distribution G_{dz} where $i \in I_{dz}$ at time t. Since correlations are modeled across d we pick the metric θ to group people into cells for the basis of determining correlations (we use the same cells that we use to determine group people for hospital and physician office visit claims). Denote these cells based on θ by z_θ. Then for each cell z_θ denote the empirical rank correlation between claims of type d and type d' by $\rho_{z_\theta}(d, d')$. Then, for a given individual i we determine the joint distribution of claims across D for year t, denoted $H_{it}(\cdot)$, by combining i's marginal distributions for all d at t using $\rho_{z_\theta}(d, d')$:

$$\Psi : G_{iDt} \times \rho_{z_{\theta_{it}}}(D, D') \rightarrow H_{it}$$

Here, G_{iDt} refers to the set of marginal distributions $G_{idt} \forall d \in D$ and $\rho_{z_{\theta_{it}}}(D, D')$ is the set of all pairwise correlations $\rho_{z_{\theta_{it}}}(d, d') \forall (d, d') \in D^2$. In estimation we perform Ψ by using a Gaussian copula to combine the marginal distribution with the rank correlations, a process which we describe momentarily.

The final part of the cost model maps the joint distribution H_{it} of the vector of total claims C over the four categories into a distribution of out of pocket expenditures for each plan. For the HDHP we construct a mapping from the vector of claims C to out of pocket expenditures OOP_j:

$$\Omega_j : C \rightarrow OOP_j$$

This mapping takes a given draw of claims from H_{it} and converts it into the out of pocket expenditures an individual would have for those claims in plan j. This mapping accounts for plan-specific features such as the deductible, co-insurance, co-payments, and out of pocket maximums listed in table A-2. We test the mapping Ω_j on the actual realizations of the claims vector C to verify that our mapping comes close to reconstructing the true mapping. Our mapping is necessarily simpler

[59]It is important to use rank correlations here to properly combine these marginal distribution into a joint distribution. Linear correlation would not translate empirical correlations to this joint distribution appropriately.

and omits things like emergency room co-payments and out of network claims. We constructed our mapping with and without these omitted categories to ensure they did not lead to an incremental increase in precision. We find that our categorization of claims into the four categories in C passed through our mapping Ω_j closely approximates the true mapping from claims to out-of-pocket expenses. Further, we find that it is important to model all four categories described above: removing any of the four makes Ω_j less accurate.

Once we have a draw of OOP_{ijt} for each i (claim draw from H_{it} passed through Ω_j) we map individual out of pocket expenditures into family out of pocket expenditures. For families with less than two members this involves adding up all the within family OOP_{ijt}. For families with more than three members there are family level restrictions on deductible paid and out-of-pocket maximums that we adjust for. Define a family k as a collection of individuals i_k and the set of families as K. Then for a given family out-of-pocket expenditures are generated:

$$\Gamma_j : OOP_{i_k,jt} \rightarrow OOP_{kjt}$$

To create the final object of interest, the family-plan-time specific distribution of out of pocket expenditures $F_{kjt}(\cdot)$, we pass the total cost distributions H_{it} through Ω_j and combine families through Γ_j. $F_{kjt}(\cdot)$ is then used as an input into the choice model that represents each family's information set over future medical expenses at the time of plan choice. Figure B23 outlines the primary components of the cost model pictorially to provide a high-level overview and to ease exposition.

We note that the decision to do the cost model by grouping individuals into cells, rather then by specifying a more continuous form, has costs and benefits. The cost is that all individuals within a given cell for a given type of claims are treated identically. The benefit is that our method produces local cost estimates for each individual that are not impacted by the combination of functional form and the health risk of medically different individuals. Also, the method we use allows for flexible modeling across claims categories. Finally, we note that we map the empirical distribution of claims to a continuous representation because this is convenient for building in correlations in the next step. The continuous distributions we generate very closely fit the actual empirical distribution of claims across these four categories.

Cost Model Identification and Estimation. The cost model is identified based on the two assumptions of (i) no moral hazard / selection based on private information and (ii) that individuals within the same cells for claims d have the same ex ante distribution of total claims in that category. Once these assumptions are made, the model uses the detailed medical data, the Johns Hopkins predictive algorithm, and the plan-specific mappings for out of pocket expenditures to generate the the final output $F_{kjt}(\cdot)$. These assumptions, and corresponding robustness analyses, are discussed at more length in the main text.

Once we group individuals into cells for each of the four claims categories, there are two statistical components to estimation. First, we need to generate the continuous marginal distribution of claims for each cell z in claim category d, G_{dz}. To do this, we fit the empirical distribution of claims $G_{I_{dz}}$ to a Weibull distribution with a mass of values at 0. We use the Weibull distribution instead of the log-normal distribution, which is traditionally used to model medical expenditures, because we find that the log-normal distribution over-predicts large claims in the data while the Weibull does not. For each d and z the claims greater than zero are estimated with a maximum likelihood fit to the Weibull distribution:

$$\max_{(\alpha_{dz},\beta_{dz})} \Pi_{i\in I_{dz}} \frac{\beta_{dz}}{\alpha_{dz}} (\frac{c_{id}}{\alpha_{dz}})^{\beta_{dz}-1} e^{-(\frac{c_{id}}{\alpha_{dz}})^{\beta_{dz}}}$$

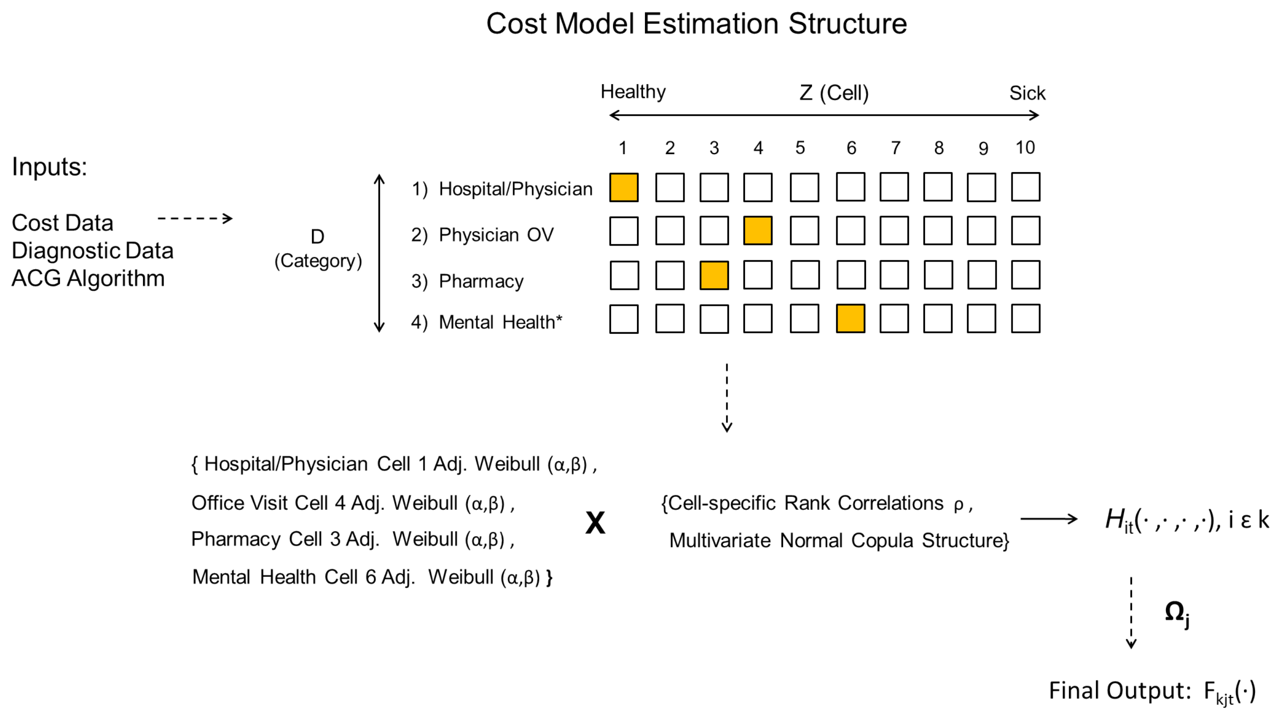

Figure B23: This figure outlines the primary steps of the cost model described in Appendix B. It moves from the initial inputs of cost data, diagnostic data, and the ACG algorithm to the final output F_{kjt} which is the family, plan, time specific distribution of out-of-pocket expenditures that enters the choice model for each family. The figure depicts an example individual in the top segment, corresponding to one cell in each category of medical expenditures. The last part of the model maps the expenditures for all individuals in one family into the final distribution F_{kjt}.

Here, $\hat{\alpha_{dz}}$ and $\hat{\beta_{dz}}$ are the shape and scale parameters that characterize the Weibull distribution. Denoting this distribution $W(\hat{\alpha_{dz}}, \hat{\beta_{dz}})$ the estimated distribution $\hat{G_{dz}}$ is formed by combining this with the estimated mass at zero claims, which is the empirical likelihood:

$$\hat{G_{dz}}(c) = \begin{cases} G_{I_{dz}}(0) & \text{if } c = 0 \\ G_{I_{dz}}(0) + \frac{W(\hat{\alpha_{dz}}, \hat{\beta_{dz}})(c)}{1 - G_{I_{dz}}(0)} & \text{if } c > 0 \end{cases}$$

Again, we use the notation $\hat{G_{iDt}}$ to represent the set of marginal distributions for i over the categories d: the distribution for each d depends on the cell z an individual i is in at t. We combine the distributions $\hat{G_{iDt}}$ for a given i and t into the joint distribution H_{it} using a Gaussian copula method for the mapping Ψ. Intuitively, this amounts to assuming a parametric form for correlation across $\hat{G_{iDt}}$ equivalent to that from a standard normal distribution with correlations equal to empirical rank correlations $\rho_{z_{\theta_{it}}}(D, D')$ described in the previous section. Let $\Phi^i_{1|2|3|4}$ denote the standard multivariate normal distribution with pairwise correlations $\rho_{z_{\theta_{it}}}(D, D')$ for all pairings of the four claims categories D. Then an individual's joint distribution of non-zero claims is:

$$\hat{H_{i,t}}(\cdot) = \Phi_{1|2|3|4}(\Phi_1^{-1}(\hat{G_{id_1t}}), \Phi_2^{-1}(\hat{G_{id_2t}}), \Phi_3^{-1}(\hat{G_{id_3t}}), \Phi_4^{-1}(\hat{G_{id_4t}})))$$

Above, Φ_d is the standard marginal normal distribution for each d. $\hat{H}_{i,t}$ is the joint distribution of claims across the four claims categories for each individual in each time period. After this is estimated, we determine our final object of interest $F_{kjt}(\cdot)$ by simulating K multivariate draws from $\hat{H}_{i,t}$ for each i and t, and passing these values through the plan-specific total claims to out of pocket mapping Ω_j and the individual to family out of pocket mapping Γ_j. The simulated $F_{kjt}(\cdot)$ for each k, j, and t is then used as an input into estimation of the choice model.

New Employees. For the first-stage full population model that compares new employees to existing employees to identify the extent of inertia, we need to estimate F_{kj} for new families. Unlike for existing families, we don't observe past medical diagnoses / claims for these families, we just observe these things after they join the firm and after they have made their first health plan choice with the firm. We deal with this issue with a simple process that creates an expected ex ante health status measure. We backdate health status in a Bayesian manner: if a consumer has health status x ex post we construct ex ante health status y as an empirical mixture distribution $f(y|x)$. $f(y|x)$ is estimated empirically and can be thought of as a reverse transition probability (if you are x in period 2, what is the probability you were y in period 1?). Then, for each possible ex ante y, we use the distributions of out-of-pocket expenditures F estimated from the cost model for that type. Thus, the actual distribution used for such employees is described by $\int_{x \in X} f(y|x)F(y)dy$. The actual cost model estimates $F(y)$ do not include new employees and leverages actual claims data for employees who have a past observed year of this data.

C Appendix: Choice Model Identification and Estimation

This appendix describes the algorithm by which we estimate the parameters of the choice model. The corresponding section in the text provided a high-level overview of this algorithm and outlined the estimation assumptions we make regarding choice model fundamentals and their links to observable data.

We estimate the choice model using a random coefficients probit simulated maximum likelihood approach similar to that summarized in Train (2009) and to that used in Handel (2013). The simulated maximum likelihood estimation approach has the minimum variance for a consistent and asymptotically normal estimator, while not being too computationally burdensome in our framework. We set up a likelihood function to predict the health choices of consumers in t_4. The maximum likelihood estimator selects the parameter values that maximize the similarity between actual choices and choices simulated with the parameters.

First, the estimator simulates Q draws for each family from the distribution of health expenditures output from the cost model, F_k for each family. The estimator also simulates D draws for each family-year from the distribution of the random coefficient γ_k, as well as from the distribution of idiosyncratic preference shocks ϵ_{kj}.

We define θ as the full set of model parameters of interest for the full / primary specification in Section 4:[60]

$$\theta \equiv (\mu_\gamma, \delta, \sigma_\gamma, \sigma_\epsilon, \eta_1, \eta_0, \beta).$$

We denote θ_{dk} as one draw derived from these parameters for each family, including the parameters that are constant across draws (e.g., for observable heterogeneity in γ or η) and those which change with each draw (unobservable heterogeneity in γ and ϵ):[61]

$$\theta_{dk} \equiv (\gamma_k, \epsilon_{kJ}, \eta_k, \beta)$$

Denote θ_{Dk} as the set of all D simulated parameter draws for family k. For each $\theta_{dk} \in \theta Dk$, the estimator uses all Q health draws to compute family-plan-specific expected utilities U_{dkj} following the choice model outlined earlier in section 4. Given these expected utilities for each θ_{dk}, we simulate the probability of choosing plan j^* in each period using a smoothed accept-reject function with the form:

$$Pr_{dk}(j = j^*) = \frac{\left(\frac{\frac{1}{-U_{dkj^*}}(\cdot)}{\Sigma_J \frac{1}{-U_{skj}}(\cdot)}\right)^\tau}{\Sigma_{\hat{j}}\left(\frac{\frac{1}{-U_{sk\hat{j}}}(\cdot)}{\Sigma_J \frac{1}{-U_{skj}}(\cdot)}\right)^\tau}$$

This smoothed accept-reject methodology follows that outlined in Train (2009) with some slight modifications to account for the expected utility specification. In theory, conditional on θ_{dk}, we would want to pick the j that maximizes U_{kj} for each family, and then average over D to get final choice probabilities. However, doing this leads to a likelihood function with flat regions, because for small changes in the estimated parameters θ, the discrete choice made does not change. The smoothing function above mimics this process for CARA utility functions: as the smoothing parameter τ becomes large the smoothed Accept-Reject simulator becomes almost identical to the

[60] While we discuss estimation for the full model, the logic extends easily to the other specifications estimated in this paper.

[61] Here, we collapse the parameters determining γ_k and η_k into those factors to keep the notation parsimonious.

true accept-reject simulator just described, where the actual utility-maximizing option is chosen with probability one. By choosing τ to be large, an individual will always choose j^* when $\frac{1}{-U_{kj^*}} > \frac{1}{-U_{kj}} \forall j \neq j^*$. The smoothing function is modified from the logit smoothing function in Train (2009) for two reasons: (i) CARA utilities are negative, so the choice should correspond to the utility with the lowest absolute value and (ii) the logit form requires exponentiating the expected utility, which in our case is already the sum of exponential functions (from CARA). This double exponentiating leads to computational issues that our specification overcomes, without any true content change since both models approach the true accept-reject function.

Denote any choice made $\mathbf{j}$ and the set of such choices as $\mathbf{J}$. In the limit as τ grows large the probability of a given $\mathbf{j}$ will either approach 1 or 0 for a given simulated draw d and family k. For all D simulation draws we compute the choice for k with the smoothed accept-reject simulator, denoted $\mathbf{j}_{dk}$. For any set of parameter values θ_{Sk} the probability that the model predicts $\mathbf{j}$ will be chosen by k is:

$$\hat{P}_k^{\mathbf{j}}(\theta, F_{kj}, X_{kt}^A, X_{kt}^B, \mathbf{Z}') = \Sigma_{d\in D}\mathbf{1}[\mathbf{j} = \mathbf{j}_{dk}]$$

Let $\hat{P}_k^{\mathbf{j}}(\theta)$ be shorthand notation for $\hat{P}_k^{\mathbf{j}}(\theta, F_{kj}, X_{kt}^A, X_{kt}^B, \mathbf{Z}')$. Conditional on these probabilities for each k, the simulated log-likelihood value for parameters θ is:

$$SLL(\theta) = \Sigma_{k\in K}\Sigma_{\mathbf{j}\in\mathbf{J}} d_{k\mathbf{j}}\ ln\hat{P}_k^{\mathbf{j}}$$

Here $d_{k\mathbf{j}}$ is an indicator function equal to one if the actual choice made by family k was $\mathbf{j}$. Then the maximum simulated likelihood estimator (MSLE) is the value of θ in the parameter space Θ that maximizes $SLL(\theta)$. In the results presented in the text, we choose $Q = 50$, $S = 50$, and $\tau = 6$, all values large enough such that the estimated parameters vary little in response to changes.

C.1 Model Implementation and Standard Errors

We implement the estimation algorithm above with the KNITRO constrained optimization package in Matlab. One challenge in non-linear optimization is to ensure that the algorithm finds a global maximum of the likelihood function rather than a local maximum. To this end, we run each model 12 times where, for each model run, the initial parameter values that the optimizer begins its search from are randomly selected from a wide range of reasonable potential values. This allows for robustness with respect to the event that the optimizer finds a local maximum far from the global maximum for a given vector of starting values. We then take the estimates from each of these 12 runs, and select the estimates that have the highest likelihood function value, implying that they are the best estimates (equal to or closest to a global maximum). We ran informal checks to ensure that, for each model, multiple starting values converged to very similar parameters similar to those with the highest likelihood function value, to ensure that we were obtaining robust results.

We compute the standard errors, provided in Appendix E, with a block bootstrap method. This methodology is simple though computationally intensive. First, we construct 50 separate samples, each the same size as our estimation sample, composed of consumers randomly drawn, with replacement, from our actual estimation sample. We then run each model, for 8 different starting values, for each of these 50 bootstrapped samples (implying 400 total estimation runs per model). The 8 starting values are drawn randomly from wide ranges centered at the actual parameter estimates. For each model, and each of the 50 bootstrapped samples, we choose the parameter estimates that have the highest likelihood function value across the 8 runs. This is the final estimate for each bootstrapped sample. Finally, we take these 50 final estimates, across the bootstrapped samples, and calculate the 2.5th and 97.5th percentiles for each parameter and statistic (we actually use the 4th and 96th percentiles given that 50 is a discrete number). Those percentiles are then, respectively, the upper and lower bounds of the 95% confidence intervals presented in Appendix E. See e.g., Bertrand et al. (2004) for an extended discussion of block bootstrap standard errors.

Finally, it is important to note that the 95% confidence intervals presented in Appendix E should really be interpreted as outer bounds on the true 95% intervals, due to computational issues with non-linear optimization. Due to time and computational constraints, we could only run each of the 50 bootstrap sample runs 8 times, instead of 12. In addition, we could not check each of these bootstrapped runs with the same amount of informal checks as for the primary estimates. This implies that, in certain cases, it is possible that one or several of the 50 estimates for each of the bootstrapped samples are not attaining a global maximum. In this case, e.g., it is possible that 45 of the 50 final estimates are attaining global maxima, while 5 are not. As a result, it is possible that the confidence intervals reported are quite wide due to computational uncertainty, even though the 45 runs that attain the global maximum have results that are quite close together. In essence, in cases where computational issues / uncertainty lead to a final estimate for a bootstrapped sample that is not a global maximum, the confidence intervals will look wide (because of these outlier / incorrect final estimates) when most estimates are quite similar. One solution to this issue would be to run each of the models more times (say 12 or 20) for each bootstrapped sample. This would lead to fewer computational concerns, but would take 1.5 to 2.5 times as long, which is substantial since the standard errors for one model take 7-10 days to run.

As a result, the confidence intervals presented should be thought of as outer bounds on the true 95% CIs. This means that for the models where these bounds are tight, the standard error results are conclusive / compelling since the true 95% CI lies in between these already tight bounds. In cases where the CI is very wide, this means that the true 95% CI lies in that wide range, and that we cannot draw meaningful conclusions due to computational uncertainty in all likelihood. Of course, it is possible the true CI is wide, but, in cases where 46 out of 50 bootstrapped parameter estimates are tight and four are outliers (without substantial variations in the underlying samples) this suggests that computational uncertainty is at fault for the wide bounds.

D Appendix: Equilibrium with Two Types of Competing Plans

The primary empirical analysis discussed in the text is for an insurance market where there is a basic government option provided and insurers compete to provide supplemental insurance. As noted in the text, this setup is in the spirit of Einav et al. (2010b). An alternative setup we describe in Section 2 and in Section 5 is that where insurers compete to offer two types of insurance plans simultaneously (so costs for both types of plans must break even with premiums in equilibrium). This latter setup is in the spirit of recent work by Handel et al. (2015) studying equilibrium in insurance exchanges. In an example, Veiga and Weyl (2015) illustrate how these two types of setups can lead to markedly different results, primarily because when costs are endogenized for basic coverage the costs incurred by each plan are similar to total expected costs, while when coverage is supplemental costs are similar only to incremental spending in the supplemental coverage. Thus, the costs faced by generous coverage in the Handel et al. (2015) setup are substantially larger than those when the coverage insurers compete to offer is supplemental. This makes it more likely that equilibrium will unravel towards less generous coverage, because incremental premiums for generous coverage must reflect this larger cost difference.

The analysis in Section 2 considered the choice to buy incremental insurance from a competitive market or stick with a baseline option. Our comparative statics for key how micro-foundations interact with friction-reducing and risk-adjustment policies (and how those foundations determine equilibrium in the absence of such policies) remains the same in the case of more than one type of priced plan. The primary change is that both the high and low coverage plans must account for sorting based on costs in premium setting, whereas in the supplemental insurance case there is no premium for baseline coverage, so it does not adjust along with endogenous sorting. In practice, as shown in Weyl and Veiga (2015) and Handel et al. (2015), this internalization of costs by both plan types leads to an order of magnitude higher of unraveling in the market, conditional on the same population consumer micro-foundations.

We briefly illustrate this for a choice between two plans, a low-coverage plan L providing only and a high-coverage plan H. If both plans are priced in competitive markets (as in Weyl and Veiga (2015) and Handel et al. (2015)), each plan needs to internalize the full cost of its own consumers.

We relate our six potentially relevant dimensions of heterogeneity to our original setup as follows:

$$c = c^H - c^L,\ s = s^H - s^L,\ f = f^H - f^L \text{ and } P = P^H - P^L.$$

Since for each plan type the price equals the average cost of the individuals selecting the respective plan, the price differential equals

$$\begin{aligned} P &= E_{\geq P}\left(c^H\right) - E_{<P}\left(c^L\right) \\ &= E_{\geq P}\left(c\right) - \left[E_{<P}\left(c^L\right) - E_{\geq P}\left(c^L\right)\right]. \end{aligned}$$

The second term captures the difference in baseline coverage costs between those actually buying the low-coverage plan relative to those buying the high-coverage plan. If the baseline coverage costs are independent of the sorting of individuals, the previous equilibrium analysis entirely generalizes. If not, we need to take into account how the policy affects the selection based on the full cost into both plans.[62] Similarly, when evaluating policy interventions, the re-sorting based on the full cost in both plans determines the new equilibrium prices. The welfare analysis naturally generalizes

[62]If both plans insure the same underlying risk but differ in their overall coverage, we have "adverse selection" into the high-coverage contract, both for the baseline and supplemental coverage, i.e., $E_{\geq P}\left(c^L\right) \geq E_{<P}\left(c^L\right)$. If two plans insure different types of risk, we may well have "adverse selection" into both contracts, i.e., $E_{<P}\left(c^L\right) \geq E_{\geq P}\left(c^L\right)$.

since the change in total welfare only depends on the change in the differential surplus (as long as the purchase of baseline coverage is mandated). That is,

$$\begin{aligned}\mathcal{W} &= (1-G(P))\,E_{\geq P}\left(s^{H}\right)+G(P)\,E_{<P}\left(s^{L}\right) \\ &= (1-G(P))\,E_{\geq P}(s)+E\left(s^{L}\right).\end{aligned}$$

See Handel et al. (2015) and Weyl and Veiga (2015) for a much more complete discussion of equilibrium in markets with multiple tiers of competitively priced plans, and how they compare to the market with baseline coverage and privately-provided supplemental coverage. For this paper, it is only important to note that the comparative statics will be the same directionally, regardless, though of course the threshold for what makes a market unravel vs. not it much lower in the markets with two or more types of priced plans.

In Section 2.5 we presented simulations to illustrate the relationship between market micro-foundations and different policy recommendations, in the Einav et al. (2010b) style market with one priced supplemental plan. Here, in Table D1 we present analogous results for the market with two priced plans. The underlying simulation micro-foundations for each scenario are the same as those described in the main text in Table 2.

In the supplemental market described in Section 2.5, for the scenarios where the distribution of surplus was high relative to costs, the equilibrium held together and friction-reducing policies were welfare improving. In the market for two priced plans, this is not the case. With high mean and variance of frictions the case with high mean and variance of surplus has quantity equal to 0.55. When frictions are reduced, either by 50% or 100% the market completely unravels, in contrast to the supplemental market. This is for the case where the variance in costs is high. For the other two scenarios presented in Table D1, with low variance in costs, low mean surplus, and low or high surplus variance, the results have a similar flavor across the range of frictions present and friction policies. With high mean frictions, the market holds together and quantity provided is high. But, when the mean level of frictions is low, or policies are in place to reduce the high mean frictions, the market fully unravels and no generous insurance is purchased in equilibrium.

These results imply that the market with two priced plans is much more likely to unravel for a given set of micro-foundations. As a result, in this style market, policies to reduce frictions are more likely to be welfare decreasing than in the market with one competitively priced supplemental plan. While the mean and variance of surplus relative to the mean and variance of costs is still a crucial determinant of whether friction-reducing policies will be good or bad, now because of the nature of the market the distribution of insurance must be higher relative to the distribution of costs in order for the market to function and in order for friction-reducing policies to be welfare positive.

A corresponding implication is that the threshold for risk-adjustment that is necessary to make friction-reducing policies welfare positive is higher in the market with two priced plans. Table D2 presents market quantities and welfares for a range of interacted risk-adjustment and friction-reducing policies. As in the main text, results are presented for the case with low μ_f and high σ_f.[63] It is clear that in all cases studied, incremental risk-adjustment increases welfare and is absolutely crucial when implementing friction-reducing policies in the market. For any of the cases presented, when risk-adjustment is either partially effective ($\beta = 0.5$) or not present ($\beta = 0$) friction-reducing policies reduce equilibrium coverage and increase adverse selection. However, when full risk-adjustment is present, friction-reducing policies improve equilibrium quantity and welfare in

[63] Note that when the mean level of frictions are increased, the equilibrium is less likely to unravel, we present this case so it can be directly compared to the supplemental equilibrium in the text.

Simulations-Two Priced Plans			
Equilibrium Quantities			
	Low σ_c Low μ_s Low σ_s	Low σ_c Low μ_s High σ_s	High σ_c High μ_s High σ_s
	Full Frictions		
High μ_f, High σ_f	0.83	0.79	0.55
High μ_f, Low σ_f	0.9	0	0
Low μ_f, High σ_f	0.33	0.28	0
Low μ_f, Low σ_f	0	0	0
No Frictions	0	0	0
	Half Frictions		
High μ_f, High σ_f	0	0	0
High μ_f, Low σ_f	0	0	0
Low μ_f, High σ_f	0	0	0
Low μ_f, Low σ_f	0	0	0
No Frictions	0	0	0

Table D1: This table presents the proportion of the market purchasing full insurance in equilibrium, for a range of underlying population micro-foundations. These results are for an insurance exchange where two types of plans are offered competitively.

the market.

Thus, the same underlying intuition holds for markets with two priced plans, but the threshold for what constitutes 'enough' risk-adjustment to implement friction-reducing policies is much higher because of the higher potential for adverse selection. This distinction is generally interesting, and reflects the underlying notion that, as the mean and variance of population costs becomes high relative to the mean and variance of surplus from risk protection, friction-reducing policies are more likely to be welfare -decreasing and more risk-adjustment is required for them to be welfare-increasing.

In addition to presenting these simulations, we also conduct the analog to our empirical analysis in the text for the case of two priced plans. Section 5 lays out the model for insurer competition in both the Einav et al. (2010b) and Handel et al. (2015) cases. Since the mean and variance of costs are high relative to surplus in our empirical application, it is highly likely that the market will unravel except for cases with very high frictions or very effective risk-adjustment.

Figure D shows market equilibrium for the baseline case where $\alpha = 0$ and $\beta = 0$. The average cost line for generous coverage always lies above the demand curve, even in this case where substantial mean frictions push people towards that coverage. The high mean and variance of consumer costs, relative to their surplus from incremental coverage, leads to this scenario, which we also see in the simulation in Section 2. Not surprisingly, when frictions are partially and fully removed in figures D24 and D25 there is still no positive equilibrium market share of more generous coverage, which is expected given that the frictions we estimate push consumers toward that coverage.

There is some hope for maintaining generous coverage when there is insurer risk-adjustment.

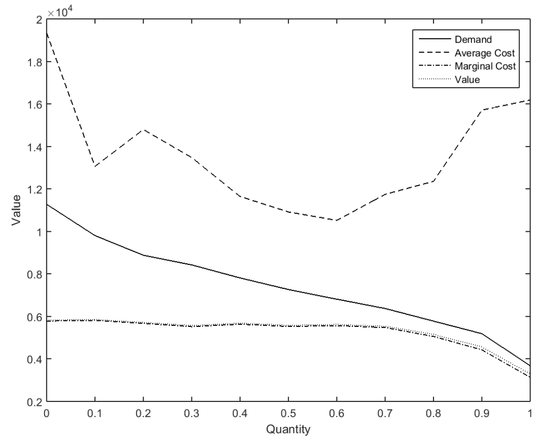

Figure D24: Market Equilibrium Including Information Frictions

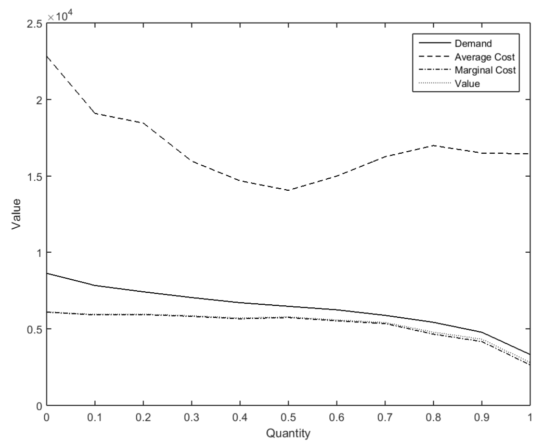

Figure D25: Market Equilibrium with Partial Information Frictions

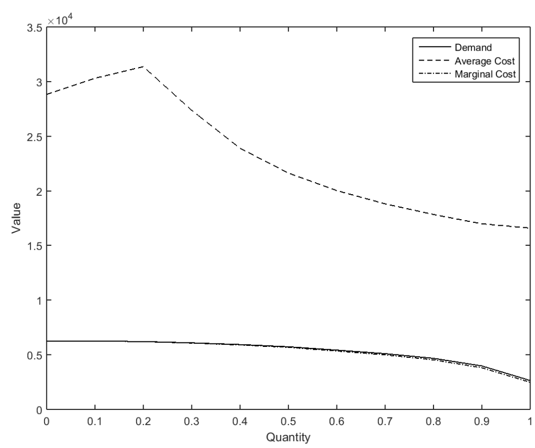

Figure D26: Market Equilibrium without Information Frictions

Simulations-Two Priced Plans Risk-Adjustment Quantity (% Surplus Achieved)			
	Low σ_c Low μ_s High σ_s	High σ_c Low μ_s High σ_s	High σ_c High μ_s High σ_s
		No Risk-Adjustment ($\beta = 0$)	
Full Frictions	0.28 (35%)	0 (0%)	0 (0%)
Half Frictions	0 (0%)	0 (0%)	0 (0%)
No Frictions	0 (0%)	0 (0%)	0 (0%)
		Partial Risk-Adjustment ($\beta = .5$)	
Full Frictions	0.45 (50%)	0.01 (2%)	0.25 (30%)
Half Frictions	0.07 (11%)	0 (0%)	0 (0%)
No Frictions	0 (0%)	0 (0%)	0 (0%)
		Full Risk-Adjustment ($\beta = 1$)	
Full Frictions	0.58 (64%)	0.57 (66%)	0.68 (72%)
Half Frictions	0.64 (72%)	0.59 (72%)	0.77 (81%)
No Frictions	0.71 (86%)	0.58 (75%)	0.94 (97%)

Table D2: This table presents equilibrium quantity sold, and proportion of total surplus achieved, as a function of the underlying risk-adjustment (β) and friction-reducing policies (α). The entire table considers the case of low μ_f and high σ_f. Results presented are for the market with two competitively priced plans.

Figure D shows that some coverage is possible with full frictions and with either partial or full risk-adjustment. When frictions are removed, even with full risk-adjustment there is full unraveling of the market: this is because the cost of the average consumer for the family tier we study is higher than the top-end value of insurance coverage, given the way that the insurance contracts are set up relative to one another. Handel et al. (2015) shows that equilibrium in the market is harder to maintain the closer the two types of coverage are relative to one another, precisely for this reason.

Thus, with the limited surplus estimated in our environment from risk-protection, and the closeness of the two types of insurance contracts relative to average costs, the market outcome in our environment is almost always full unraveling. There are a few reasons why we might not see this in practice. First, consumers typically receive subsidies to purchase insurance coverage, either from the government in exchanges or from their employer in employer provided insurance. Though one typical principle of managed competition is that consumers receive a lump sum subsidy and pay the full marginal cost of generous coverage, in practice in many exchanges poorer consumers have caps on the premiums that they pay, limiting the relative premium spread between insurance contracts. The second reason is that consumers with frictions may follow decision models whereby they always choose more generous coverage no matter what. With the micro-foundations in our

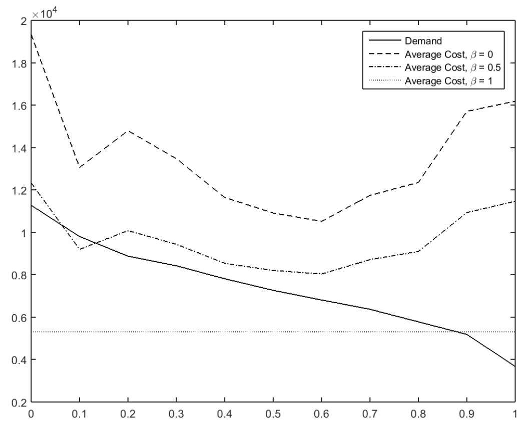

Figure D27: Market Equilibrium with full frictions and a range of risk-adjustment policies.

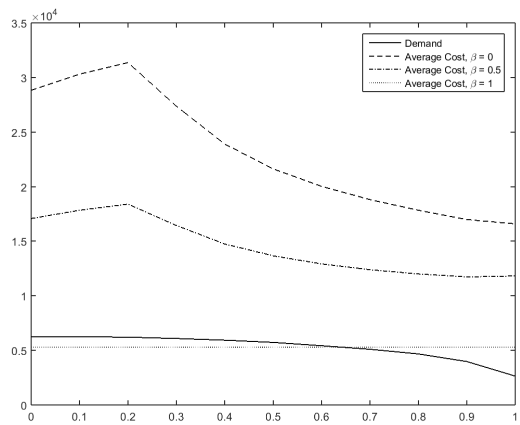

Figure D28: Market Equilibrium with no frictions and a range of risk-adjustment policies.

environment, even the presence of such consumers would not hold the equilibrium together, given the spread because average costs in the PPO and the relative generosity of that coverage, unless the consumers choosing generous coverage by mistake are the healthiest in the population.

E Appendix: Additional Analysis

Table E presents summary demographic statistics for the samples we study. The first column represents all employees who were present in our data and have complete records for at least eight months in the four years of data (t_1-t_4) that we observe.[64] The second column represents all employees who received our survey, regardless of whether or not they responded. The third column represents all employees who responded to our survey. Statistics from gender onwards represent only t_3, and use the re-weighted statistics for the second and third columns, as described in the text.

Table E2 presents the details of plan design for the two plans consumers choose between in our empirical environment. Table E4 presents the results for the simulations in Section 2.5 that are for the case of partially effective friction-reducing policies ($\alpha = 0.5$). Table E3 describes the proportion of consumers making choice mistakes in each of the simulation scenarios described in Section 2.5.

[64]We cannot provide the exact number of overall employees, to preserve the anonymity of the firm. As noted earlier, we cannot state the exact years of the data, though we note they are from a four-year period between 2008-2014.

Sample Demographics	Full Sample	Survey Recip. (Weighted)	Survey Resp. (Weighted)
N -Employees	[35,000 , 60,000]*	4500	1661
N_d - Emp.& Dep.	[105,000 , 200,000]*	11,690	4,584
t_3 PPO%	88.8	89.6	88.7
t_4 PPO%	82.7	83.0	81.6
t_3 HDHP %	11.2	10.4	11.3
t_4 HDHP %	17.3	17.0	18.4
Gender, Emp. and Dep. (% Male)	51.8	51.5	51.1
Age			
18-29	8.6%	14.9%	11.6%
30-39	41.1%	43.8%	42.7%
40-49	38.1%	32.7%	34.1%
50-59	10.9%	7.7%	10.5%
$\geq$60	1.3%	0.9%	1.2%
Income			
Tier 1 ($<$ \$100K)	12.8%	15.3%	16.2%
Tier 2 (\$100K-\$150K)	65.8%	68.5%	69.2%
Tier 3 (\$150K-\$200K)	16.7%	14.3%	12.9%
Tier 4 (\$200K+)	3.5%	1.2%	0.9%
Family Size			
1	23.0%	29.0%	20.9%
2	19.0%	19.4%	21.9%
3+	58.0%	51.6%	57.2%
Family Spending			
Mean	\$10,191	\$8,820	\$11,247
Median	\$4,275	\$3,363	\$4,305
25th	\$1,214	\$878	\$1,176
75th	\$10,948	\$9,388	\$11,555
95th	\$35,139	\$32,171	\$41,864
99th	\$87,709	\$80,370	\$87,022

Table E1: This table gives summary statistics for the employees and dependents of the firm we use data from. When not stated, statistics are for year t_4. See Handel and Kolstad (2015) for more information on the population, their information about insurance options, and the link between costs, information, surplus, and insurance choices. Note that we cannot provide the exact sample size for all employees and dependents at the firm, to preserve the anonymity of the firm (though we can discuss sample size of the specific samples used in our analysis.

Health Plan Characteristics **Family Tier**	PPO	HDHP*
Premium	$0	$0
Health Savings Account (HSA)	No	Yes
HSA Subsidy	-	[$3,000-$4,000]**
Max. HSA Contribution	-	$6,250***
Deductible	$0****	[$3,000-$4,000]**
Coinsurance (IN)	0%	10%
Coinsurance (OUT)	20%	30%
Out-of-Pocket Max.	$0****	[$6,000-$7,000]**

* We don't provide exact HDHP characteristics to help preserve firm anonymity.

**Values for family coverage tier (2+ dependents). Single employees (or w/ one dependent) have .4× (.8×) the values given here.

***Single employee legal maximum contribution is $3,100. Employees over 55 can contribute an extra $1,000 in 'catch-up.'

****For out-of-network spending, PPO has a very low deductible and out-of-pocket max. both less than $400 per person.

Table E2: This table presents key characteristics of the two primary plans offered over time at the firm we study. The PPO option has more comprehensive risk coverage while the HDHP option gives a lump sum payment to employees up front but has a lower degree of risk protection. The numbers in the main table are presented for the family tier (the majority of employees) though we also note the levels for single employees and couples below the main table.

Simulations **Mistakes in Equilibrium**	Low σ_c Low μ_s Low σ_s	Low σ_c Low μ_s High σ_s	High σ_c Low μ_s Low σ_s	High σ_c Low μ_s High σ_s	High σ_c High μ_s High σ_s
		Full Frictions			
High μ_f, High σ_f	.23 (.18)	.31 (.27)	.47 (.45)	.36 (.33)	.11 (.07)
High μ_f, Low σ_f	.56 (.56)	.61 (.61)	.50 (.50)	.43 (.43)	.09 (.09)
Low μ_f, High σ_f	.39 (.13)	.39 (.15)	.35 (.24)	.35 (.20)	.35 (.06)
Low μ_f, Low σ_f	.26 (.13)	.21 (.11)	.02 (.01)	.06 (.04)	.17 (.04)
		Half Frictions			
High μ_f, High σ_f	.21 (.18)	.28 (.26)	.44 (.42)	.34 (.32)	.09 (.06)
High μ_f, Low σ_f	.35 (.35)	.30 (.30)	.50 (.50)	.42 (.42)	.09 (.09)
Low μ_f, High σ_f	.33 (.14)	.30 (.14)	.20 (.15)	.23 (.14)	.26 (.06)
Low μ_f, Low σ_f	.17 (.09)	.11 (.06)	.01 (0)	.02 (.01)	.09 (.03)

Table E3: This table presents the proportion of consumers making mistakes when purchasing coverage, given the equilibrium price, for a range of underlying population micro-foundations.

Simulations **Results for** $\alpha = 0.5$	Low σ_c Low μ_s Low σ_s	Low σ_c Low μ_s High σ_s	High σ_c Low μ_s Low σ_s	High σ_c Low μ_s High σ_s	High σ_c High μ_s High σ_s
		Half Frictions, % Purchase			
High μ_f, High σ_f	0.94	0.92	0.86	0.9	0.97
High μ_f, Low σ_f	1	1	1	1	1
Low μ_f, High σ_f	0.63	0.57	0.34	0.41	0.72
Low μ_f, Low σ_f	0.61	0.44	0.06	0.11	0.86
No Frictions	0.45	0.39	0.06	0.11	0.91
		Half Frictions % Surplus			
High μ_f, High σ_f	0.95	0.95	0.87	0.94	0.97
High μ_f, Low σ_f	1	1	1	1	1
Low μ_f, High σ_f	0.68	0.66	0.42	0.56	0.76
Low μ_f, Low σ_f	0.71	0.60	0.10	0.25	0.94
No Frictions	0.56	0.55	0.10	0.23	0.95

Table E4: This table presents the proportion of consumers purchasing generous coverage (top half) and the proportion of first-best surplus achieved in the market (bottom half) for a range of underlying population micro-foundations and a partially effective friction-reducing policy ($\alpha = 0.5$).