

# Behavioral Economics and Health-Care Markets

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## 1 Introduction

Writing in 1963, Kenneth Arrow—the father of health-economics—explained the many ways in which markets for health-insurance and health-care services were different than other markets. Arrow’s emphasis was on how uncertainty of various types is pervasive in medical-care markets. It showed up in the form of unpredictable illness that required costly interventions, which in turn created demand for health-insurance. It showed up as uncertainty about the effect of illness on health, earnings, and recovery. And it showed up as uncertainty in the value of medical treatments themselves, not knowing product quality or the therapeutic benefit of treatment. Arrow argued that such characteristics of the medical-care market established a special place for it in economic analysis.

In this chapter, we return to themes from Arrow’s seminal work and update them with insights from behavioral economics, a field that wasn’t born at the time of his writing. Like him, we focus on insurance markets and product markets in health care. And, like Arrow, we focus on special characteristics of medical-care markets. But while his emphasis was on the importance of uncertainty in these markets, ours is on the importance of choice difficulties and biases leading to

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mistakes. Our approach overlaps with Arrow's because the presence of uncertainty increases the difficulty of choosing insurance and care wisely, and the likelihood that a health-care consumer succumbs to various forms of behavioral biases.

Indeed, health economics markets abound in difficult choices and other enablers for biases. It is not easy to choose between health insurance plans; to forecast the need for care; to assess the benefits and costs of treatment. The presence of uncertainty creates space for many biases, such as errors in statistical-reasoning, projection bias, and mis-weighting of probabilities. But special features of medical-care markets are great enablers of potential mistakes more broadly. For example, the benefits of care are often in the distant future while the costs appear now, so present bias is likely important. While, as we discuss below, the behavioral health-economics literature has done a better job of documenting choice mistakes than explaining *why* those mistakes occur, it is clear that we should not ignore these mistakes in our analyses.

Health-care economics is a broad field containing many possible specific applications of behavioral economics. To focus our chapter, we primarily analyze health-care markets rather than health more broadly. Table 1 presents a range of applications, separating ones that we cover in this handbook chapter from ones that we do not. We focus this chapter on the topics of (i) consumer insurance choices and corresponding market implications and (ii) health-care utilization choices, with corresponding normative and positive implications for the design of insurance contracts. The topics that we focus on are close in spirit to the topics discussed in Arrow (1963).

Topics that we do not cover in detail, but are fertile ground for behavioral economics research, include (i) diet; (ii) exercise; (iii) addiction; (iv) end-of-life care; (v) provider responses to financial incentives and quality programs; (vi) provider integration of information; and (vii) mechanism design in the context of the medical residency match. Many of these topics involve decisions that are either physician-directed, primarily influenced by factors other than market prices, and/or influenced by non-standard preferences. Table 1 presents examples of research on these topics.

Since health-insurance plan choice is a point of entry into decision making in the health-care sector, we start by considering this choice. Research shows that consumers leave lots of money

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**Behavioral Health Economics Applications**

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**Topics Covered**

Consumer insurance choices

Insurance impact on consumer health-care utilization

Provider-consumer joint treatment choices

Consumer adherence to medications / treatments

**Sample References**

Handel (2013)

Bhargava, Loewenstein and Sydnor (2017)

Brot-Goldberg et al. (2017)

Baicker, Mullainathan and Schwartzstein (2015)

Sokol et al. (2005)

**Topics Not Covered**

Diet

Exercise

Addiction

End-of-life care

Medical-testing decisions

Provider treatment choices

Provider responses to incentives / quality programs

Provider use of information / information technology

Residency match mechanism design

Volpp et al. (2008)

Oster (2018)

DellaVigna and Malmendier (2006)

Carrera et al. (2018)

Gruber and Koszegi (2013)

Bernheim and Rangel (2004)

Halpern et al. (2013), Sudore et al. (2017)

Kószegi (2003)

Oster, Shoulson and Dorsey (2013)

Chandra et al. (2012)

Kolstad (2013)

Rees-Jones (2018)

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Table 1: This table presents a range of behavioral health-economics applications, together with sample references.

on the table in their plan choices, sometimes thousands of dollars. This research takes several approaches to identifying poor consumer choices and to characterizing the underlying mechanisms behind those choices. It focuses on active choice issues, arising when consumers are engaged in the choice process. It also focuses on passive choice issues, arising from inertia when consumers have a default option. We discuss the implications of this body of work for questions in industrial organization such as the design and regulation of insurance markets, including the interaction between consumer choice difficulties or biases and adverse selection.

We then consider how consumers respond to changes in prices such as copayments and deductibles in their medical-treatment choices, conditional on their choice of health plan. A large and influential literature in economics notes that increases in patient cost-sharing through copayments and deductibles reduce the demand for health care. This effect is often referred to as the "price elasticity of demand for medical care" and is conventionally used by economists as a measure of moral hazard under the assumption that, by letting a low price discourage treatment, a patient reveals that the treatment has little value to them. Put differently, in the conventional model, moral hazard would point to some marginal-value care being reduced when prices increase—so there would be an adverse, but small, health cost. However, choice difficulties and biases may lead the patient to cut back on treatment that in fact is of great value, muddying the argument that the price elasticity of demand meaningfully captures the degree of moral hazard.

Key specific issues on consumer treatment choices that we discuss include (i) how patients respond to the highly non-linear structure of high-deductible health plans (which have low first-dollar coverage but generous last dollar coverage); (ii) how patients respond to increases in copayments; and (iii) patterns of patient adherence to treatment recommendations. We discuss the many potential biases and frictions that contribute to mis-behavior in these areas, as well as the empirical literature suggesting the prevalence of such mis-behavior. Following typical assumptions made in this literature, we also describe welfare implications.<sup>1</sup>

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<sup>1</sup>While we include only a very brief discussion of pre-system health behaviors like diet and exercise, see, e.g., Cawley and Ruhm (2011) for a survey covering individual behaviors in these areas. Also, since patient choices are often made jointly with physicians, we briefly discuss physician decision-making. There has been less research studying behavioral economics in the context of physician treatment decisions, likely because of the empirical difficulty

As with most work in the area of empirical behavioral economics, the positive and normative implications of key results depends on the maintained assumptions. In his book on identification, Manski (1999) discusses a tradeoff between the credibility of an empirical analysis and the assumptions required for sharp predictions. In empirical research in behavioral economics, this tradeoff is particularly relevant for welfare calculations where the researcher needs to know structural parameters whose estimation necessitates modeling assumptions about consumer decision-making. While we strive to present a healthy skepticism of the assumptions maintained in the empirical work we analyze, we also believe that relevance necessitates some use of plain and accessible language.

For example, we will refer to some decisions that consumers make as mistakes when the preponderance of evidence suggests that consumers would have been better off making another choice. However, we acknowledge the concern that consumers may respond to idiosyncratic preferences that economists and physicians observing them do not observe—we will point out the kinds of assumptions that a neoclassical observer would have to make in order to refute our preferred interpretation.

We also follow the empirical literature and assume that the correct welfare frame is that of a consumer without choice frictions or behavioral biases making a choice at the same time that he/she does in practice (e.g., during open enrollment in health-insurance markets). While we discuss this assumption in more depth throughout the chapter, we defer to the discussion of welfare and behavioral economics in Bernheim and Taubinsky (2018) for a more detailed treatment of the underlying issues.

Finally, we want to highlight the nascent nature of our topic area. Other chapters in this Handbook concern areas like retirement savings and financial markets, where the cumulative amount of knowledge on the role of mistakes (and which mistakes are important) is higher. But this makes behavioral health economics an especially exciting area in which to work going forward. We lay

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of identifying physician biases and/or mistakes separately from their (and their patients') private information. See, e.g., Chandra et al. (2012) for a survey of the literature on physician decision-making, as well as Chandra and Staiger (2017) and Chandra and Staiger (2010) for examples of physician bias in treatment decisions.

out some directions for future research in the concluding section.

## **2 Consumer Choice of Insurance**

Consumer purchase and use of health insurance are central components of their experiences in health-care markets. Insurance protects consumers from potentially crippling financial risk, and serves as a crucial intermediary between consumers and medical providers. In many settings, consumers are presented with a range of insurance options to choose from, with the goal of facilitating the best matches between consumers and plans. For instance, the health-insurance exchanges set up under the Affordable Care Act of 2010 and drug-plan markets set up under Medicare Part D in 2003 encourage private insurers to enter and compete for consumers' business. In these managed competition environments, consumers typically have many choices, in some cases up to 40 or 50. Similarly, large employers offering coverage often present employees with several choices to encourage both competition between insurers and efficient employee-plan experiences. The rationale in favor of market environments with a meaningful number of choices is clear: if consumers are well informed and make unbiased choices, having a greater number of options facilitates efficient matching, drives premiums down through increased competition, and forces insurers to improve non-pecuniary aspects of their products such as provider networks. Even in markets with single-payer systems such as the UK, many patients still choose supplemental coverage plans that have these features and require consumers to choose between alternative plans.

Yet it may be difficult for consumers to assess the many complex features of insurance plans, and to synthesize those assessments into plan choices. There is ample empirical evidence that consumers have difficulty making active choices in insurance markets, as well as passive choices where inertia plays a role and consumers are placed into a default option if they take no new action. As detailed in subsequent sections, consumers often leave hundreds, and sometimes thousands, of dollars on the table in their plan choices. They frequently lack or fail to process key pieces of information about financial and non-financial plan characteristics. In certain cases, they

even choose options that are financially dominated by another plan in their choice set, losing a significant amount of money with certainty. Broadly, the implications of these issues are two-fold: (i) conditional on the market environment, consumers are worse off due to poorer plan matches and (ii) insurance prices and products do not improve to the extent they would in competitive markets with frictionless and bias-free consumers.

The literature on consumer choice in insurance markets has exploded over the past decade and continues to be very active. In addition to being an important market with a lot at stake, researchers have been attracted to health insurance due to the paradigm-shifting ACA (and related) reform efforts. Finally, researchers have been able to obtain individual-level datasets with detailed information on health-risk heterogeneity and insurance purchases. This latter feature allows researchers to infer what consumers *should* choose much more easily than they can in standard product markets, making health-insurance markets an excellent context to study behavioral economics.

Overall, this literature shows several clear patterns. First, consumers often leave meaningful sums of money on the table when making active insurance choices. Though there are many potential explanations, primary ones include (see, e.g., Handel and Schwartzstein (2018)) (i) information frictions, including costs of processing information, and (ii) mental gaps, including biases in integrating information and limited insurance competence. Consumer choices become even worse when a previously chosen option is the default: inertia causes consumers to lose substantial sums of money, above and beyond what they lose in active choice settings. Consumer choice mistakes also have important implications for the industrial organization of health-insurance markets and, more broadly, the regulation of health-insurance markets. We now discuss each of these areas in turn.

## **2.1 Demand for Insurance**

### **2.1.1 Simple Model**

Most prior research studying the potential for consumer mistakes in health insurance markets focuses on broadly documenting these mistakes and, when possible, linking them to specific micro-

foundations. We begin with a simple model (borrowed from Handel, Kolstad and Spinnewijn (2015)) that nests most of these micro-foundations: this model is especially useful when thinking about the market implications of behavioral consumers, which we discuss later in this chapter.

Consider a consumer choosing between two insurance options. Define  $w_i$  as a consumer's willingness-to-pay for plan 1 relative to plan 2. Denote a consumer's true value for plan 1 relative to plan 2 as  $v_i$ . Here, we define true value as the ex ante willingness-to-pay for a consumer with no information frictions or behavioral biases. Given this, a consumer's relative surplus will be the difference between a consumer's true valuation and the expected cost to the insurer  $c_i$ ; that is, surplus equals  $v_i - c_i$ . Positive surplus from one insurance plan relative to another could reflect, e.g., increased risk protection for a risk averse consumer, or a broader provider network granting access to preferable providers.

Sources of consumer mistakes in this setup are reflected in the difference between willingness-to-pay, which impacts consumer demand, and true consumer ex ante value, which impacts consumer welfare:

$$\varepsilon_i = w_i - v_i. \tag{1}$$

A positive value of  $\varepsilon_i$  implies that the entire set of frictions and biases a consumer faces causes her to overvalue plan 1 relative to plan 2 by  $\varepsilon_i$ . This impacts purchases and market outcomes: a consumer purchases plan 1 if  $w_i$  exceeds the relative price of plan 1,  $\Delta P$ , but, in a frictionless and bias-free market, a consumer should only purchase that plan if  $v_i > \Delta P$ .<sup>2</sup> This simple model is useful to have in mind during our discussion of more complex micro-founded models, which propose specific underpinnings of  $\varepsilon_i$  and  $v_i$ . Additionally, it is useful for thinking about the sufficient statistics necessary to evaluate different policy interventions, something we discuss at the end of this section. Also, this framework relates closely to the behavioral hazard framework discussed for consumer medical-treatment choices in the next section of this chapter.

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<sup>2</sup>This presumes that a consumer chooses one plan or the other. This could be, e.g., because of a fully-enforced individual mandate, as specified by the Affordable Care Act.

This framework, by definition, assumes that the “correct” welfare criterion, both for the consumer and policymaker, is derived from consumers’ decision utility at the time of choice assuming they were to make that choice (i) without behavioral biases and (ii) without information frictions. Throughout this chapter, we abide by this criterion because (i) it is parsimonious in modeling the distinction between revealed preference with and without both frictions and biases and (ii) it is the approach followed (at least implicitly) by much of the empirical literatures in behavioral health economics, behavioral industrial organization, and behavioral public finance. See, e.g., Koszegi and Rabin (2008) and Bernheim and Taubinsky (2018) for an extended discussion of welfare economics for behavioral consumers.

When empirical behavioral papers model specific mechanisms underlying poor consumer-plan choices, the typical starting point is a model of a rational frictionless expected utility maximizing consumer. Behavioral models typically modify the baseline expected-utility setup to reflect distinct choice biases and/or frictions. There are many ways such modifications can be made, some sticking closely to the classical expected-utility framework and others moving further away.

### **2.1.2 Modified Expected Utility to Study Active Choices: Handel and Kolstad (2015b)**

The first model we discuss, from Handel and Kolstad (2015b), closely follows a classical expected utility setup. This allows the authors to show how bringing additional data to bear on consumers’ lack of knowledge (interpreted as the result of information frictions) impacts the conclusions that are drawn, relative to assuming biases and frictions away in a classical expected-utility framework.

The consumer’s problem is to choose a plan  $j$  from set  $\mathcal{J}$ . To analyze this problem, we will first consider consumer utility in a given insurance plan conditional on a specific health risk outcome (ex post utility). Then, we will discuss *ex ante* consumer utility from an insurance plan, i.e., in advance of knowing the health-risk outcome.

Consumer  $i$ ’s ex post utility in health plan  $j$  is:

$$u(W_i - P_{ij} + \pi_j(\psi_j, \mu_i) - s, \gamma_i). \tag{2}$$

$u$  is assumed to be a concave utility function, implying that consumers have diminishing marginal utility for wealth and are risk averse. A typical functional form assumption is constant absolute risk aversion (CARA), meaning that the curvature of the utility function doesn't depend on baseline wealth. This is a one-parameter functional form where  $\gamma$  describes the degree of curvature:  $\gamma$  close to 0 means low curvature (risk-neutral) while high  $\gamma$  means high curvature (quite risk averse). This ex-post utility includes several components, some of which are the same regardless of health during the year.  $W_i$  is consumer wealth and  $P_{ij}$  is the premium contribution an individual  $i$  pays in plan  $j$ .  $\pi_j$  reflects the consumer's value for non-financial plan characteristics, such as provider networks or tax-advantaged health-savings accounts: this depends on plan characteristics  $\psi_j$  and a consumer's health type  $\mu_i$ . In this formulation, each of these components is assumed to be independent of the health-risk realization.<sup>3</sup>

Finally, the payment  $s$  is the consumer's out-of-pocket payment for health care, given an ex post realization of their health risk. This is the element consumers have uncertainty about, which is why, given risk aversion, insurance is valuable for them ex ante.

We now turn to *ex ante* consumer utility, which captures their expected utility from an insurance plan. Assume that a consumer faces uncertainty about their out-of-pocket spending in a given plan  $j$ , following the probability distribution  $f_{ij}(s|\psi_j, \mu_i)$ . The distribution of payments depends on the plan design and the consumer's health-risk type. Given this uncertainty, a consumer's expected utility for plan  $j$  is:

$$U_{ij} = \int_0^{\infty} f_{ij}(s|\psi_j, \mu_i) u(W_i - P_{ij} + \pi_j(\psi_j, \mu_i) - s, \gamma_i) ds. \quad (3)$$

The expected utility function averages the utility the consumer gets across her possible health-risk realizations. For example, if consumers are very risk-averse, then high  $s$  outcomes in a plan will strongly discourage the consumer from choosing that plan. Within this setup, the consumer will choose the plan  $j$  that maximizes her expected utility  $U_{ij}$ . If we map this frictionless and bias-free

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<sup>3</sup>In certain settings, one may want to model  $\pi$  as a function of the ex post risk realization as well, since provider networks and health risk interact. We don't do so here for simplicity.

expected utility framework to our earlier simple model of plan choice ( $\varepsilon_i = 0$ ), both the consumer's relative willingness-to-pay for one plan vs. another ( $w_i$ ) as well as her true welfare ( $v_i$ ) line up with the difference in certainty equivalents implied by  $U_{ij}$  and  $U_{ij}'$ .

Handel and Kolstad (2015*b*) depart from this baseline expected utility model by allowing for the consumer's beliefs (notated with "hats") to deviate from what they would be under full information and rational expectations:

$$\widehat{U}_{ij} = \int_0^{\infty} f_{ij}(s|\widehat{\psi}_{i,j}, \widehat{\mu}_i) u(W_i - P_{ij} + \widehat{\pi}_{i,j}(\widehat{\psi}_{i,j}, \widehat{\mu}_i) - s, \gamma_i) ds \quad (4)$$

Here, beliefs about plan characteristics, health risk, and health benefits are modeled allowing for both population-level and individual-level departures from the rational-model values.

Empirically, this framework allows for departures from baseline beliefs and information due to information frictions or biases more broadly. These frictions and biases may result from consumers not having easy access to key information; consumers not attending to readily available information; or consumers having difficulty integrating certain types of information into decisions. Handel and Kolstad consider data from a large firm with over 50,000 employees where employees choose between two plans: a broad network PPO plan with no premium and no (in network) cost sharing, and a high-deductible plan with the same network and a linked health savings account subsidy (essentially a reverse premium). The paper presents descriptive evidence showing that consumers seem to substantially under-purchase the high-deductible plan (HDHP) based on its financial value relative to the simpler PPO option. The standard non-behavioral explanation is that these purchasing patterns reflect consumer risk aversion—but the degree of risk aversion necessary to rationalize these choices is very high.

Given this backdrop, the authors implemented a comprehensive survey to measure consumer information sets shortly after they make plan choices during open enrollment. The survey asks multiple choice questions to consumers about all aspects of plan choice, including perceptions

about the health savings account subsidy, provider networks, and financial characteristics such as deductibles or coinsurance. In addition, the survey asks about perceived hassle costs of enrolling in a high-deductible plan where medical bills and health savings accounts may involve time and hassle costs relative to the hassle-free PPO option. The survey is linked to enrollment and detailed claims data at the individual-level, allowing the authors to study how individual choices relate to limited information. The authors show that consumers who lack knowledge about the high-deductible plan relative to the PPO plan are more likely to leave substantial sums of money on the table in their plan choices. The key point is that this money left on the table is not due to risk aversion, but to frictions or biases that result in limited knowledge.

The primary structural model the authors estimate is a baseline expected utility model with shifters that reflect changes in willingness-to-pay for the high-deductible plan as a function of limited information about that plan (as measured in the survey). This is very similar to the theoretical model in equation (4) but incorporates measures of limited information in a specific way. The main specification is:

$$U_{ij} = \int_0^{\infty} f_{ij}(s)u_i(x_{ij})ds \quad (5)$$

$$u_i(x) = -\frac{1}{\gamma_i(\mathbf{D}_i)}e^{-\gamma_i(\mathbf{D}_i)x} \quad (6)$$

$$x_{ij} = W_i - P_{ij} - s + \eta(\mathbf{D}_i)\mathbf{1}_{j_t=j_{t-1}} + \mathbf{Z}'_i\beta\mathbf{I}_{HDHP} + \epsilon_{ij}. \quad (7)$$

Here,  $U_{ij}$  is an expected utility function for a risk averse consumer, following the model just discussed. Equation (6) describes the functional form used to implement the constant absolute risk aversion model.  $x_{ij}$  measures the outcome (translated into monetary units) for each consumer during the year, given a realization of their health uncertainty.  $\eta$  is a term that addresses consumer inertia, modeled as an implied switching cost. Risk aversion  $\gamma$  and inertia  $\eta$  both vary with observable demographics  $D_i$ .

The authors include indicator variables related to consumers' information sets in the vector  $\mathbf{Z}$ .

For each question, they construct indicator variables for ‘informed’, ‘uninformed’ or ‘not sure’ answers as well as variables derived from answers to questions about hassle costs and knowledge of own health expenditures.  $Z = 0$  indicates that a consumer is perfectly informed, while  $Z = 1$  indicates that a consumer lacks information on a certain dimension. The coefficient  $\beta$  then measures the impact of that lack of information on willingness-to-pay for the high-deductible plan relative to the less complex PPO option.

This empirical approach to studying the impact of consumer frictions and biases has several advantages and disadvantages. One advantage is that measuring effective consumer information sets with surveys is often feasible. Another advantage is that the approach is simple, in the sense that the estimates tell us about the impact of survey-measured limited information on willingness-to-pay for different options. One disadvantage is that it doesn’t posit a specific structural mechanism for how limited information impacts choices: a more structured version would allow for answers to survey questions to imply something specific about the precise nature of beliefs. But it is also difficult to link the responses directly to belief objects. This disadvantage makes it difficult to assess whether specific policy interventions to improve consumers’ choices would be successful. Another potential disadvantage is that the baseline model used is a specific expected utility model that does not capture behavioral notions of how consumers respond to risk and uncertainty, which is an important topic.<sup>4</sup>

Handel and Kolstad (2015*b*) offer several results on the knowledge consumers lack and the resulting amount of money they leave on the table. The most influential gaps in knowledge are about available providers and treatments, and the perceived time and hassle costs for the high-deductible plan. For example, a consumer who incorrectly believes that the PPO option grants greater medical access than the high-deductible plan (they grant the same access in reality) is willing to pay \$2,267 more on average for the PPO over the one-year period of the insurance contract than a correctly

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<sup>4</sup>While we are unaware of empirical papers studying non-standard consumer responses to risk and uncertainty in health insurance, Barseghyan et al. (2013) study non-linear probability weighting for consumers choosing car and property insurance policies and Grubb and Osborne (2015) studies overconfidence and myopia in cellular phone markets. These projects structurally identify alternative choice models, but typically assume full consumer information to do so. It should be possible to combine the Handel and Kolstad (2015*b*) approach with these others.

informed consumer. Aggregating across all included measures for incomplete knowledge, the average consumer is willing to pay \$1,694 more for the PPO relative to a fully informed consumer with zero perceived hassle costs. Consumer perceptions of relative hassle costs, which likely overstate true hassle costs, have a major impact, equaling approximately \$100 per perceived extra hour of time spent on plan hassle.<sup>5</sup>

Next, they find that including measures of consumer information into the model together with risk aversion significantly changes estimates of risk aversion. Framed in terms of a simple hypothetical gamble, a consumer with baseline model risk aversion (where information frictions are not taken into account) would be indifferent between taking on a gamble in which he gains \$1000 with a 50 percent chance and loses \$367 with a 50 percent chance. In other words, he would have to be paid a risk premium of roughly \$633 in expectation to take this risky bet. In the primary model with survey variables included, the consumer is instead found to be indifferent between taking on a gamble with a \$1000 gain and \$913 loss (with 50% chance of each). This has meaningful implications for policy, for example altering conclusions of the benefits of forcing consumers into high-deductible plans.

### **2.1.3 Dominated Choices and Mechanisms Behind Mistakes in Active Choices: Bhargava, Loewenstein and Sydnor (2017)**

Bhargava, Loewenstein and Sydnor (2017) also study mistakes in health insurance plan choice, but focus more on empirically identifying the mechanisms underlying those mistakes. They use data from a large firm with approximately 24,000 employees, where employees chose from a flexible menu with up to 48 different possible plans. For almost all employees, choosing the low deductible (most generous plan) is strictly financially dominated by another plan, meaning that for *any possible* level of total health expenditures (insurer + insuree) during the year, the consumer is better off financially in that other plan.<sup>6</sup> Since the low deductible option is financially dominated, no

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<sup>5</sup>The authors consider different possible welfare interpretations of perceived time and hassle costs. Perceived costs are higher than stated costs, suggesting that some component of perceived time and hassle costs are not actually experienced by people once they enroll in the high-deductible plan.

<sup>6</sup>Typically, researchers discuss one plan as dominated by another only when networks of providers are also identical

consumer in a standard expected utility model should choose that option. The authors document that the majority of employees do in fact choose a financially dominated plan, losing on average \$400 relative to choosing otherwise equivalent high-deductible options.

The authors conduct a series of lab experiments to study why the employees might be choosing dominated plans. They consider the following possibilities:

1. **Menu Complexity:** The authors define menu complexity based on the number of plans in the choice set  $N$  and the number of attributes  $K$  that define each plan. As either  $N$  or  $K$  increases, the authors say that the menu becomes more complex.
2. **Alternative Preferences:** The authors consider preferences that depart from the baseline expected utility model. Consumers may, for example, gain some extra value from not making an out-of-pocket payment. This could occur if consumers have (perceived) liquidity constraints, a desire for budget predictability, or just a distaste for making payments related to medical care.
3. **Insurance Literacy:** If consumers have low insurance literacy, then they may have incorrect beliefs about plan costs. For example, if a consumer does not appropriately understand what an out-of-pocket maximum is, he may project that a plan has substantial tail-spending risk when it in fact does not. A good illustration of this possibility comes from evidence in Loewenstein et al. (2013), which presents results from surveys where consumers are (i) asked whether they think they understand key insurance concepts (e.g., deductibles, coinsurance, and the out-of-pocket maximum) and (ii) tested to see if they correctly work with these concepts in practice. The paper finds, e.g., that 93% of consumers claim to understand the out-of-pocket maximum while only 55% of those consumers actually pass a simple comprehension test for this feature (it shows analogous results for the deductible, coinsurance, and copays). In the Handel and Kolstad (2015*b*) notation, this kind of limited insurance literacy could, e.g., enter into mis-specified beliefs about out-of-pocket spending  $f_{ij}(s|\widehat{\psi}_{ij}, \widehat{\mu}_i)$

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between the options, so that there is no standard rationale to choose the dominated option.

resulting from a poor understanding of how insurance plan characteristics map to final payments.

In their first lab experiment, Bhargava, Loewenstein and Sydnor (2017) randomly give their online subjects menus with different levels of complexity that always include some dominated options. The authors find that even when they reduce plan menus from 12 plans and 2 attributes to 4 plans and 1 attribute, consumers continue to choose dominated plans at a similar rate, suggesting that menu complexity / size is not a primary reason for dominated-plan choices in this particular context.

Their second experiment exposed consumers to high and low clarity presentations. The low clarity presentation was similar to that faced by employees at the firm, while the high clarity presentation included additional information about the plan options that highlighted the financial consequences of those options. The fraction of consumers choosing dominated plans is substantially reduced but not eliminated under the high-clarity presentation—the fraction choosing dominated plans goes from 48% in the low-clarity presentation to 18% in the high-clarity presentation. This suggests that non-standard preferences play a relatively minor (though still potentially meaningful) role in consumers choosing dominated plans. Instead, explanation three, low insurance literacy, seems to be the primary driver of dominated-plan choices in their setting: when consumers receive substantial help translating plan menus into simple value propositions, they are much less likely to choose dominated plan options. The authors also elicit measures of insurance competence from study participants, and find that low insurance competence is correlated with choosing dominated plans.

#### **2.1.4 Additional Empirical Evidence on Mistakes in Active Choices**

Both the Handel and Kolstad (2015*b*) and Bhargava, Loewenstein and Sydnor (2017) papers document mistakes in active insurance purchases. There are a number of complementary studies that provide evidence of similar mistakes. Abaluck and Gruber (2011) show that consumers forego substantial savings in Medicare Part D choices, controlling for spending risk, risk preferences, and

average brand preferences. Medicare Part D is an especially interesting market to study from a behavioral economics standpoint because consumers have many options (typically around 40) and may not have the time, information, or knowledge to understand the subtleties of what differentiates these options from one another. In addition, Medicare Part D, which was introduced in 2006, was set up with an underlying premise that rational and well-informed consumers would choose effectively from these many options, delivering value to themselves and disciplining the market. If consumers do not choose effectively from the options in the market, the motivation for this style of insurance reform is called into question.

Abaluck and Gruber (2011) find that a key reason consumers lose money on their plan choices is that they overweight premiums by a factor of 5 to 1 relative to expected out-of-pocket spending. (This finding is consistent with results from more recent work, both in Medicare Part D and other health insurance markets.) Abaluck and Gruber (2011) model this bias with a modified expected utility model, similar in spirit to that described above from Handel and Kolstad (2015*b*), where the key modification is allowing the weight consumers place on premiums to differ from the weight they place on expected out-of-pocket spending. Further work is necessary to better understand the sources of this bias. Potential explanations include, but are not limited to, consumers having better information on premiums than other characteristics (premiums are known with certainty and are prominently posted); consumers having greater relative comprehension of what premiums mean; and consumers being overconfident that out-of-pocket spending will be low.

Heiss et al. (2010) also study consumer choice quality in Medicare Part D and find results that are consistent with those from Abaluck and Gruber (2011). They find that fewer than 10% of consumers enroll in a plan that is *ex post* optimal and that consumers on average lose roughly \$300 per year in their plan choices. Ketcham et al. (2012) show similar patterns in Part D plan choices and also study whether consumers learn to make better choices over time. They find evidence of poor consumer choices but, leveraging panel data, find that consumers may make better choices over time as they gain experience in the market. Specifically, they find that consumer overspending is reduced, on average, by \$298 in their second year in the Part D market relative to their first. Some

of this may be due to plan switching and some to plans delivering better value over time.

### **2.1.5 Interventions to Improve Active Choices**

While there are several papers documenting how health-insurance consumers make mistakes in their active choices, there are fewer papers that study interventions to help consumers make better enrollment decisions. Ericson and Starc (2016) study consumer choice on the Massachusetts Health Insurance Exchange. The authors study a natural experiment where the exchange implemented meaningful product standardization reforms. Specifically, moving from one year to the next, the exchange significantly reduced the scope for plans to differ along many financial attributes (e.g., deductibles and coinsurance rates). The exchange complemented this change with a web design that helped consumers compare plans with the same financial attributes, though the plans could still differ on premiums and provider networks.

The authors model two channels by which product standardization impacts allocations: (i) the availability channel, whereby the products in the market change and (ii) the valuation channel, whereby consumers' decision weights attached to different plan attributes change. When standardization impacts the valuation channel, consumers' decision-utilities change, e.g., because consumers attend more to certain attributes. To complement their empirical analyses, the authors run an experiment to differentiate between impacts of product standardization itself and the improved presentation of the choice set via a new web design. The experiment finds that product standardization matters, but that the better presentation of the standardized options also improves choices conditional on the choice set.

Several other papers study interventions to help improve consumers' insurance choices, though there is still much to be done in this literature. Kling et al. (2012) studies a targeted intervention to seniors choosing in the Medicare Part D market. The authors run a randomized control trial where members of the the treatment group get individually-tailored letters with key information about how they could switch Part D plans and save money in the process. This intervention increased plan switching, with those in the treatment group switching 28% of the time and those in the

control group 17% of the time. Those in the treatment group had an average decline in spending of approximately \$100.

Abaluck and Gruber (2016b) study the plan choices of Oregon school district employees and begin by showing that consumers leave substantial sums of money on the table in their plan choices, consistent with their findings on choices in Medicare Part D. The authors then study several interventions to help improve these choices. First, they study whether forcing some employees to make active choices substantially reduces their foregone savings. They identify the effect of active choice by comparing the choices of consumers whose prior plans were canceled to those of consumers whose plans were not canceled. They find little effect, presumably because consumers' active choices were privately suboptimal. Next, they study an information intervention that gave employees access to an individually-tailored online tool giving them help shopping for insurance plans. They also find that this intervention has essentially no impact on plan-choice quality, though they note some key issues with the implementation of the online tool that they study. Their third intervention, choice-set regulation by the school district, is effective in improving consumer welfare. This regulation removed the lower quality options from the choice set without removing too much match-specific value between insurers and consumers. We discuss this analysis in greater detail later in this chapter.

An important caveat to studies that investigate interventions to improve consumer choices in health-insurance markets (e.g. online tools or mailed letters) is that their results depend on the specific qualities and features of those interventions and are fairly context dependent. Without a robust literature that studies a range of carefully documented interventions it is difficult to derive general lessons on the potential for such interventions to improve consumer choices.

### **2.1.6 Mistakes in Passive Choices: Inertia**

While the papers we have discussed so far show that consumers have difficulty making active choices in insurance markets, there has been as much if not more empirical research on consumer inertia and the significant value consumers leave on the table in *passive choice settings*—where the

default is that they will be continue to be enrolled in their prior option if they make no new choice. Consumer inertia reduces the quality of consumer choices in such settings, as products evolve over time and consumers do not adjust accordingly.

Handel (2013) studies inertia using data from a large employer that spans six years (2004-2009). The employer changed the menu of options employees could choose from during the middle of this time frame and forced all employees to make active (non-default) choices from this new menu of options. Following that forced active choice, consumers had a default option of their previously chosen plan, despite the fact that the plan premiums and features changed significantly over time. The paper presents several pieces of descriptive evidence suggesting that inertia causes consumers to leave meaningful sums of money on the table. First, one product changed over time such that it became dominated by other options (similar to Bhargava, Loewenstein and Sydnor (2017)) and, despite losing over a thousand dollars for sure, consumers continued to enroll in the newly dominated plan when it was their default option. Second, the active choices that new enrollees made were significantly better (in terms of money left on the table) than the choices of similar incumbent employees who had a default option. While active choices are far from perfect, choices become worse in an environment with a suboptimal default option.

The paper estimates a structural model of consumer inertia, modeled as a switching or adjustment cost that could result from consumers having research / paperwork costs of switching or learning costs of using a new plan. The expected utility framework is similar to that in Handel and Kolstad (2015*b*) as described in equations (5)-(7). A simplified version of the Handel (2013) analog to equation (7), representing the money at stake for consumers for each health state, is:

$$x_{ij} = W_i - P_{ij} - s + \eta(\mathbf{X}_i^B)\mathbf{1}_{j_t=j_{t-1}} + \epsilon_{ij}. \quad (8)$$

Inertia is quantified by the amount of money consumers are willing to leave on the table to stick with their incumbent plan. In effect, the premium for the incumbent plan is lowered by  $\eta$  for consumers in this model.  $\eta$  is allowed to depend on observable characteristics,  $X$ , including other benefits choices consumers make (such as flexible spending account choices that must be actively

made every year). Inertia in this environment (and most health insurance environments) could result from any of the following micro-foundations:

1. **Switching Costs:** Consumers could incur paperwork or hassle costs of switching plans. Consumers may also incur adjustment costs to learn how to use their new plan, or costs associated with needing to switch care providers. While this last cost (of switching providers) is not an issue in the Handel (2013) analysis, such costs will be relevant in many settings.
2. **Search Costs:** Consumers could incur costs of searching through the different available plan options to determine if they want to switch. Typically, this would be modeled as a two stage model (as in Ho, Hogan and Scott Morton (2017) described below) where consumers first decide whether to search and then decide whether to switch after searching.
3. **Inattention:** Consumers could be inattentive. They could rationally decide not to engage in the search process because search is too costly relative to expected benefits. Or they could less rationally neglect potential benefits of carefully considering plans and plan options.
4. **Naive Present Bias:** Consumers could believe that they will conduct research and make a new choice right before the choice deadline, but then when the time arrives not be willing or able to invest the time and effort to do so.

Handel (2013) does not distinguish between these micro-foundations, but shows how welfare conclusions are sensitive to the micro-foundation. In particular, his welfare analysis allows for a range of results that depend on whether or not inertia primarily results from a rational response to costs (e.g., of search) or a less rational response to perceived benefits and/or perceived costs.<sup>7</sup>

The paper finds that consumers exhibit significant inertia: on average, consumers with a default option are estimated to leave \$2,032 on the table annually to stay with their default. Consumers

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<sup>7</sup>The welfare analysis presumes the same normative standard for a consumer's "true" plan valuation discussed earlier in this chapter, i.e., the valuation of a rational and frictionless consumer with no biases at the time of choice. The welfare costs of inertia are added on top of this framework: the author investigates a range of assumptions spanning from the case where estimated costs are all welfare-relevant when incurred to the case where estimated switching costs are not at all welfare relevant.

who also make active flexible spending account elections leave an average of \$551 less on the table.<sup>8</sup> Families, who have more money at stake, leave \$751 more on the table than single employees. There is no evidence that recent health shocks lead to active choices. The paper studies counterfactual policies where the extent of inertia is reduced by some proportion and consumers re-choose plans in the market. In the partial equilibrium analysis where plan prices do not adjust from re-sorting, a 75% reduction in the magnitude of inertia improves consumer welfare by 5.2% of paid premiums. Later in this section, when we discuss the market implications of poor choices, we will discuss the case where prices are allowed to re-adjust as consumers make better choices due to reduced inertia.

A range of other papers study inertia in health insurance markets and show that it causes meaningful financial losses for consumers. Ho, Hogan and Scott Morton (2017) study inertia in Medicare Part D with a model of inattention. They model consumers with a default option making choices in two stages. First, they decide whether or not to engage with the market. This decision is influenced by a series of shocks (e.g., changes to the premium of their current plan) related to the market and their default option. Second, consumers who decide to engage in the market choose a plan following a standard active discrete choice model, where consumer  $i$ 's utility for option  $j$  is denoted by  $u_{i,j}$ .

As the market evolves over time, consumers costlessly learn about how their current plan changes but have to pay a cost  $\varepsilon$  to learn about how the characteristics of other plans change. Consumers choose to pay this cost if the expected benefit of doing so outweighs the cost:

$$\mathbb{E} \left[ \max_{j=1, \dots, J} u_{i,j,t+1} | \bar{X}_{i,k,t+1} \right] - u_{i,k,t+1} > \varepsilon_{i,t}.$$

Here, plan  $k$  is the choice a consumer is currently enrolled in and  $\bar{X}_{i,k,t+1}$  includes the known characteristics for that plan. The expectation is taken over the characteristics of other plans that the consumer discovers if she pays the cost to search through the set of available plans. If the

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<sup>8</sup>Consumers who elect to make a flexible spending account (FSA) contribution must do so actively each year—they cannot default into their previous year's contribution. As a result, when a consumer elects to contribute to an FSA, she is making an active-benefits decision.

consumer pays the cost to search then she learns the characteristics of all plans in the market. The consumer is more likely to search if (i) she has a health shock that changes the value she receives from different plans; (ii) the characteristics of her current plan change; and/or (iii) she receives a signal that the market significantly evolved to make search valuable.

Empirically, the authors estimate this model without fully specifying consumers' beliefs about other options in the market prior to search. They model consumer attention as being a function of whether they experience shocks ( $v$ ) that cause them to pay attention:

$$v_{i,t} = v_{i,p,t}\beta_1 + v_{i,c,t}\beta_2 + v_{i,h,t}\beta_3 + v_{i,e,t}.$$

Here,  $v_p$  equals 1 if there is a premium increase for a consumer's own plan that exceeds the median weighted increase in the market;  $v_c$  equals 1 if there is a meaningful change to the out-of-pocket coverage characteristics for a consumer's own plan;  $v_h$  equals 1 if the consumer experienced an acute health shock in the past year, e.g., a significant increase in drug spending; and  $v_e$  is a random shock that spurs consumer search. With this framework, a consumer searches if her composite shock  $v$  is greater than some threshold value (related to  $\varepsilon_{i,t}$  above). Then, if the consumer searches, she picks the plan that maximizes her expected utility, with full updated knowledge of all plan characteristics. If the consumer does not search then she remains in the plan that she is already enrolled in.

Ho, Hogan and Scott Morton (2017) find substantial inertia in the Medicare Part D context: only approximately 10% of consumers switch plans each year and leave a lot of money on the table by not switching. Consistent with the model of inattention, consumers are more likely to switch when their own plan features (e.g., premium or cost-sharing) change but are less likely to search when alternative plan features change by similar amounts. The paper then studies how insurers price given the degree of inertia in the market, which we discuss later in this section. It is interesting to note that Handel (2013) and Ho, Hogan and Scott Morton (2017) use similar data and identification strategies to study inertia, but assume different micro-foundations. Future work that empirically distinguishes between mechanisms for inertia will be valuable in this literature

(Handel and Schwartzstein (2018)).

A range of other papers also document inertia in Medicare Part D. These papers include Ericson (2014), Polyakova (2016), Heiss, McFadden and Winter (2016), and Abaluck and Gruber (2016a), with each approaching the inertia question from a distinct angle. In addition, Abaluck and Gruber (2016a) find limited evidence that consumers learn to shop effectively for plans over time, contrary to the findings in Ketcham et al. (2012). Finally, in the large employer and Medicaid managed care contexts, respectively, Strombom, Buchmueller and Feldstein (2002) and Marton, Yelowitz and Talbert (2015) both show significant value left on the table due to consumer inertia.

Research on inertia in health-insurance choices is also consistent with powerful default effects in other domains. See, e.g., Beshears et al. (2018) for examples in household finance.

## **2.2 Implications for Insurance Markets and Their Regulation**

The literature on consumer choice in insurance markets shows several patterns. First, consumers often leave meaningful sums of money on the table when making active insurance choices. While some of this may reflect search or other welfare-relevant costs, the magnitudes involved make it likely that many consumers are making mistakes. Second, inertia causes consumers to leave even more on the table when their previously chosen option is the default. These patterns have important implications for the industrial organization of health insurance markets and, more broadly, the regulation of health-insurance markets.

### **2.2.1 Welfare Revisited**

One key theme in the Handel, Kolstad and Spinnewijn (2015) paper, and others in both the behavioral health and broader empirical behavioral economics literature, is the subtlety involved in measuring welfare in markets where consumers make mistakes (see, e.g., Bernheim and Rangel (2009) for an extended treatment). The Handel, Kolstad and Spinnewijn (2015) framework models true consumer welfare as the *ex ante* value that a consumer without behavioral biases and choice frictions would derive from a given insurance plan, while demand reflects *ex ante* willingness-to-pay.

Drawing a distinction between demand and welfare is crucial in policy analyses in markets with behavioral consumers: Handel and Kolstad (2015*b*), Abaluck and Gruber (2016*b*), Abaluck and Gruber (2016*a*), and Handel (2013) all differentiate between demand and welfare; Baicker, Mulainathan and Schwartzstein (2015) (which we discuss in the next section) uses a similar framework to analyze consumer demand for health care. Crucially, if researchers don't distinguish between demand and welfare, they are implicitly assuming that consumers choose the options that make them best off, contradicting much of the empirical evidence in this literature.<sup>9</sup>

Figure 1 illustrates a simple and common case where the distinction between demand and welfare is crucial. The figure considers a population of consumers choosing between a comprehensive and basic insurance option. The demand curve reflects the incremental willingness-to-pay between the comprehensive and basic options, and the welfare curve reflects the incremental consumer value. Quantity reflects the proportion of consumers in the market purchasing comprehensive coverage. All other consumers are assumed to choose the basic option, e.g., because of a fully-enforced individual mandate that rules out being uninsured. The welfare curve is drawn conditional on demand, in the sense that it presents the welfare for consumers at that quantity point of the demand curve. To keep things simple, we assume that marginal cost is constant across all consumers. This could reflect the case of perfect risk adjustment, for example, where insurers receive transfers for enrolling sick consumers and pay transfers for enrolling healthy consumers. In this framework, which follows that in Einav, Finkelstein and Cullen (2010) and Handel, Kolstad and Spinnewijn (2015), the welfare curve reflects the benefit consumers gain from incremental insurance, and the marginal cost curve reflects the social cost of that incremental insurance.

Competitive equilibrium occurs in the market where demand crosses the average cost curve (which here is the same as the marginal cost curve because it is flat). In the Einav, Finkelstein and Cullen (2010) approach, also applied empirically, e.g., by Hackmann, Kolstad and Kowalski (2015), the competitive equilibrium point in this picture is the welfare-maximizing point. This is

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<sup>9</sup>See Bernheim and Taubinsky (2018) for an extended discussion of related empirical work in public finance and see that chapter, along with an article by Handel and Schwartzstein (2018), for more in-depth discussions of the theoretical and empirical assumptions typically made within such frameworks.

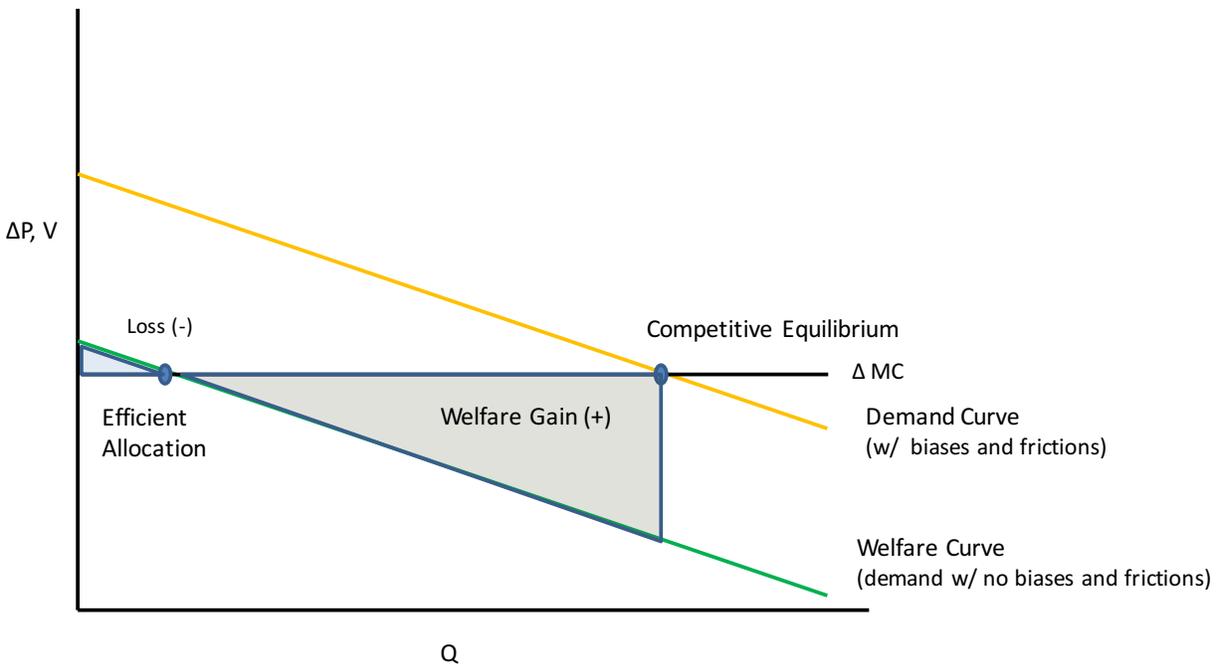


Figure 1: This figure portrays outcomes in an insurance market with two types of plans: comprehensive and basic. Demand, true welfare, and marginal cost are portrayed for comprehensive relative to basic coverage. The figure shows the welfare impact of a policy that eliminates the possibility of choosing comprehensive coverage. The policy would be welfare reducing if demand was taken to reflect welfare.

because demand is assumed to be the same as welfare. However, if consumers have frictions or biases that drive a wedge between demand and welfare, the competitive equilibrium is no longer the welfare-maximizing point. Instead, the welfare-maximizing point is the point labeled as the efficient allocation, where the welfare curve crosses the marginal cost curve. The graph illustrates a case where consumers in the population over-demand comprehensive insurance, so they have a willingness-to-pay higher than true welfare for such coverage. This is similar to the empirical case described earlier in Handel and Kolstad (2015b).

With this framework in mind, think about a policymaker who is deciding whether or not to implement a policy that removes comprehensive coverage from the market entirely. This is similar, e.g., to a firm requiring employees to enroll in high-deductible care, or a regulator removing the most comprehensive options from a market such as an ACA exchange or the Medicare Part D drug insurance market. Without modeling the wedge between welfare and demand, this policy will be

seen as strictly welfare reducing. However, with the separate modeling of demand and welfare, this policy now has the welfare effect shown in the picture, which depicts the case where the welfare gains for consumers are bigger than the welfare losses. Consumers who had erroneously been over-purchasing comprehensive coverage are now enrolled in the more preferable option, while only a small portion of consumers who would have been better off in comprehensive coverage experience welfare losses.

This simple example illustrates potential policy implications of modeling welfare separately from demand in environments with behavioral consumers. This is true in more realistic and complex settings where other issues, such as adverse selection, are a concern.

## **2.2.2 Consumer Mistakes and Adverse Selection**

Consumers' mistakes are bad for them given a specific market structure. However, empirical research has shown that in insurance markets where adverse selection is a prime concern, improving choices may ultimately make consumers worse off. This presents a challenge for policymakers considering avenues to improve consumers' decisions.

Adverse selection is an important potential inefficiency that arises in insurance markets where the costs to the insurer depend on who is insured. When sicker consumers choose more comprehensive insurance coverage, the premiums for those plans increase to reflect greater costs to the insurer. As a result, healthier consumers, who could prefer plans with greater network coverage or risk protection, may be priced out of the market.

Handel (2013) studies the interaction between inertia and adverse selection using a counterfactual analysis where, as consumer inertia is reduced, consumers pick different insurance plans and the prices of those plans adjust as a result. When inertia is reduced by 75% of its baseline estimate, the premiums for comprehensive coverage increase sharply as healthy people who had been choosing that coverage and losing value shift to less generous coverage. This leads to a death spiral, where the comprehensive plan essentially disappears from the market with an extremely high premium, and consumers who want higher coverage are forced into lower-coverage options.

Quantitatively, reduced inertia leads to a 7.7% unintended welfare *reduction* in this environment: helping consumers make better choices is bad for the sample overall.

Polyakova (2016) studies a similar question in Medicare Part D, but emphasizes that whether reduced inertia will be good or bad for consumers depends on how initial prices in the market are set. This paper shows that in Part D, where initial prices for comprehensive coverage are relatively far away from those for less generous coverage, reduced inertia actually helps the prices of more comprehensive coverage adjust downward over time (under the assumption that insurers use lagged average cost pricing). This is because initial prices were set further apart than steady-state equilibrium prices, so reduced inertia, which helps prices move more quickly towards the steady-state equilibrium, reduces the price gap. Thus, in the Part D environment, reduced inertia may both help consumers conditional on the market environment and, by lowering the price of comprehensive coverage in the market, reduce adverse selection.

Handel, Kolstad and Spinnewijn (2015) provide a general framework for studying when improved choices exacerbate adverse selection. They use the simple model given at the beginning of this insurance section to analyze a population of consumers that are heterogeneous across many dimensions: costs, willingness-to-pay, true value, and choice frictions driving a wedge between willingness-to-pay and true value. The authors derive several theoretical results for competitive insurance markets where consumers make active choices. They show that, as both the mean and variance of consumer surplus rise relative to the mean and variance of costs, improving consumer choices is more likely to be beneficial. This is because the feedback loop between costs and premiums generating adverse selection becomes dominated by improved matching of consumers to the plans they value the most. For example, if heterogeneous consumer values for insurance as a tool for risk protection are relatively large and varied, then improved decision-making facilitates large improvements to welfare through better matching. If these values are not strongly correlated with costs, then there will be limited incremental selection but substantial gains from better choices. The converse is also true: as the mean and variance of costs become more important contributors to insurance value relative to surplus from risk protection, helping consumers make better deci-

sions is worse for the market: these improved decisions cause additional adverse selection which dominates the benefit from better matching. The authors illustrate the interactions between these key objects with simulations as well as an empirical application based on Handel and Kolstad (2015*b*).

In addition to studying the pricing impacts of improved choices in competitive markets with adverse selection, several papers study how firms price in markets with inertial consumers. Ericson (2014) documents the invest-then-harvest pricing patterns in Medicare Part D, finding that firms initially set prices low in order to attract consumers and then raise prices to take advantage of consumers' inertia. Ho, Hogan and Scott Morton (2017) also study dynamic firm pricing to inertial consumers in Medicare Part D, with a model of imperfect competition. The authors find that premiums would be meaningfully reduced if inertia were removed entirely, and that the government could save approximately 550 million dollars each year in the process since they provide substantial subsidies for plan purchases. But, overall, there has been quite limited work studying how firms price to behavioral consumers in health-insurance and health-care markets. See Heidhaus and Koszegi (2018) for a broader discussion of behavioral industrial organization and some of the approaches that could be applied to studying related questions in health-care markets.

### **2.2.3 Paternalistic Interventions**

There are also important regulatory questions that directly relate to consumer-choice mistakes. Abaluck and Gruber (2016*a*) study whether including more options in the consumers' choice sets is good or bad. This is similar in spirit to the work of Bhargava, Loewenstein and Sydnor (2017) mentioned earlier, but studies a specific empirical environment to model and identify a tradeoff between improved consumer-plan matches from greater choice and increased consumer-choice errors from having more options. The authors leverage a unique data set from Oregon school district employees where each district had the opportunity to offer any combination of 13 approved plans to consumers. Thus, the overall set of plans each district could offer was fixed, but each district could curate its own set of options. As a result, both cross-sectionally and over time, the

authors observe similar consumers with a number of choices ranging from 1 to 13, drawn from the same overall set of plans.

Abaluck and Gruber (2016a) find that, in their environment, a greater number of plans is associated with worse outcomes for consumers. Using the average consumer's empirical decision function, choosing from sets with 7-8 plans leads to about \$400-\$500 more in total costs than choosing from sets with 2-3 plans. A meaningful proportion of the higher foregone savings in the larger choice sets is due to the incremental options being worse on average than those included in the choice sets with 2-3 plans. Inertia raises consumer foregone savings by approximately \$85 on average. Moreover, consumers are estimated to be quite insensitive to reducing their out-of-pocket costs. This leads to estimates of minimal consumer plan matching benefits (on average \$30) from offering 7-8 plans relative to 2-3 plans.

This result calls into question the managed competition paradigm underlying many health insurance markets. As we mention above, such markets allow many plans to enter and compete with one another, with the idea being that more plans mean greater value for consumers in terms of matching and premium competition. If instead more options confuse consumers, and allow firms to prey on them, regulators may want to curate these markets closely and serve as intermediaries between plans and consumers.<sup>10</sup>

A related topic that researchers should investigate is the extent to which targeted (or "smart") default options can help or hurt consumers. Handel and Kolstad (2015a) propose a targeted default policy and analyze the tradeoffs involved in some simulations. Targeted defaults give consumers a default option that is best matched for them, determined by an algorithm implemented by a regulator or market designer. These defaults can be tailored based on consumer health risk, risk preferences, and preferences for providers. The ability to target defaults precisely depends on the extent of data available to the regulator and her ability to use those data in forming defaults. Defaults can be implemented with different levels of aggressiveness: a very aggressive default policy would default consumers into a new plan if it improved their expected value by a little bit,

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<sup>10</sup>Certain ACA state exchanges, such as, e.g., Massachusetts and California, use this kind of model to offer more curated options.

without exposing them to more risk or changing their key providers. A less aggressive policy would require a large gain in expected value to change their plan. As defaults become more aggressive, the expected gain for the population overall is likely to increase, but the number of consumers who lose because of the policy also increases. There is currently no empirical work that we are aware of that investigates smart default policies in health-insurance markets. One interesting issue that arises is how an effective smart default policy interacts with a competitive market paradigm. On the one hand, effective smart defaults allow the market to function as advocates of managed competition intend, with many consumers choosing the best plans for them and competition creating value. On the other hand, if a regulator's algorithm is driving this competition, it calls into question whether or not insurers can game this algorithm, and whether a heavily regulated market with few options chosen by the regulator is preferable.

In Section 4 we discuss promising avenues for future behavioral research on health-insurance markets.

### **3 Treatment Choices**

Behavioral insights change how we think about health treatment choices by patients. As noted earlier, while there is an active role for physicians in what gets prescribed and why, our focus will be on consumer-driven decisions like whether to fill a prescription given the cost of doing so. In the standard model, the concern is that people will seek too much care relative to the cost of treatment because treatment is subsidized by insurance. According to this model, the inefficiency generated by insurance—the moral hazard cost of insurance—is analogous to the deadweight loss generated by below marginal cost pricing. We know from deadweight loss calculus that this inefficiency is greater when the elasticity of demand for treatment is higher: moral hazard requires that patients have heterogeneous responses to treatment and that they know these responses better than the insurer. The higher the price elasticity, the greater this heterogeneity and the more low (utility) value care is encouraged when prices are reduced.

But evidence and behavioral principles suggest that systematic biases influence treatment choices. Misutilization is not just driven by insurance, but also by mistakes. Underutilization is a concern in addition to overutilization. The inefficiency generated by the combination of biases and insurance cannot be determined only by examining the demand curve. In fact, as we will spell out below, a greater elasticity of demand for treatment may signal a greater *benefit* of expanding insurance coverage, for example if underuse is the big concern and the large price sensitivity suggests that reducing prices will in fact mitigate underuse. To really tell, we need to examine health impacts of treatments — we cannot assume the demand curve tells us everything we need to know about these impacts. Likewise, taking a step back, people may not be sophisticated enough about their own biases to demand insurance contracts that successfully counteract those biases. This means that there is room for behaviorally-minded policy interventions that improve the efficiency of insurees' treatment choices beyond what we see under equilibrium insurance contracts.

### **3.1 Consumer Demand for Treatment**

In the standard neo-classical model, a person decides whether to treat—fill a prescription, take a pill, get a procedure, etc.—by trading off the benefit  $b$  of treatment against the price  $p$ . In insurance contexts, this price reflects copays, coinsurance rates, or deductibles. In other contexts, this may reflect a market price. Treatment benefits are net of non-pecuniary costs, such as side effects, and as such are not restricted to be positive. In this model, a person treats whenever  $b > p$  and does not treat whenever  $b < p$ . This model says that if a person chooses not to treat at a given price he must value treatment at less than the price.

Evidence on actual treatment choices challenges this perspective. While we will note caveats in describing some of the evidence below, in many situations people seem not to treat when benefits likely exceed the price; in others people seek treatments that are very unlikely to help. Treatment choices are also sensitive to nudges and respond in inconsistent ways to different price levers. In short, rather than choosing to treat according to whether  $b > p$ , people seem to treat according to

whether

$$b + \varepsilon > p, \tag{9}$$

where, as described below,  $\varepsilon$  is viewed as varying systematically as a function of disease, treatment, prices, and nudges. In Equation (9),  $\varepsilon$  captures misbehavior due to mistakes or “behavioral hazard” (Baicker, Mullainathan and Schwartzstein, 2015). When  $\varepsilon > 0$  behavioral hazard increases people’s tendency to treat (e.g., in seeking ineffective treatment for back pain) and when  $\varepsilon < 0$  behavioral hazard reduces people’s tendency to treat (e.g., in not adhering to effective diabetes treatment). Behavioral hazard can reflect misunderstandings of price levers, such as non-linear schedules. It may also differ across individuals.

This framework—which builds on Mullainathan, Schwartzstein and Congdon (2012)—nests behavioral models where people misbehave because of mistakes, capturing a divide between preference as revealed by choice and utility as it is experienced, or between “decision utility” and “experienced utility” (Kahneman, Wakker and Sarin, 1997).<sup>11</sup> While  $b - p$  affects the experienced utility of taking the pill or treatment, individuals instead choose as if  $b + \varepsilon - p$  affects this utility. For example, Baicker, Mullainathan and Schwartzstein (2015) show how it nests models of present-bias, inattention, and false beliefs. Viewing  $\varepsilon$ , e.g., as a function of  $p$ , it also nests models where people misreact to price levers.<sup>12</sup>

### 3.1.1 Over and Underutilization

Behavioral first principles suggest many reasons why people are likely to misbehave in health treatment decisions. The benefits of care are often in the distant future while the costs appear now, so present bias (Laibson, 1997; O’Donoghue and Rabin, 1999) is likely important (Newhouse, 2006). Symptoms of many conditions like elevated glucose levels for diabetics are not salient, so

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<sup>11</sup>Gabaix and Farhi (2017) develop a more general framework that nests previous contributions.

<sup>12</sup>Note that non-standard preferences, for example where anticipation and anxiety are important contributors to utility (Koszegi 2003), influence choices through their impact on how people view benefits  $b$ —they do not necessarily lead to mistakes.

inattention—modeled in economics by, e.g., DellaVigna (2009), Bordalo, Gennaioli and Shleifer (2012, 2013), Koszegi and Szeidl (2013), Schwartzstein (2014), Gabaix (2014)—often matters (Osterberg and Blaschke, 2005). Given the complicated nature of many decisions and the scope for bad theories in this context to persist (Eyster and Rabin, 2014; Gagnon-Bartsch, Rabin and Schwartzstein, 2017), false beliefs likely play an important role (Pauly and Blavin, 2008).

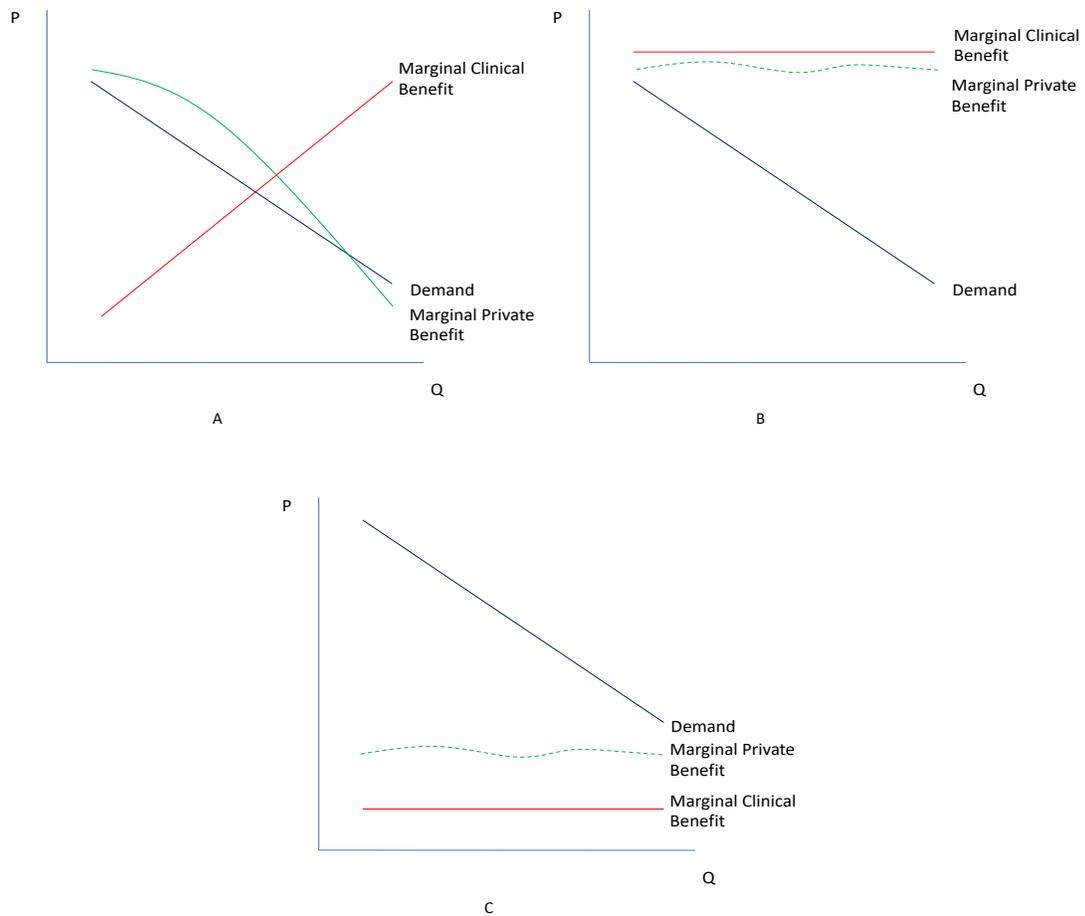
A variety of evidence also points to such misbehavior—systematically non-zero wedges,  $\varepsilon$ , between willingness to pay and true consumer value/welfare—but the interpretation of that evidence is non-trivial. To see the potential difficulty, let’s index patients by  $i \in \mathcal{I}$  and de-compose the benefit of treatment for patient  $i$  as  $b_i = v_i(h_i)$ . Here,  $h_i$  is the net (of side effects) clinical benefit of treatment for patient  $i$  and  $v_i$  represents how much patient  $i$  cares about that benefit. The marginal clinical benefit of treatment at price  $p$  is then  $\mathbb{E}[h_i | b_i + \varepsilon_i = p]$ , while the marginal private benefit (true value/consumer welfare) is  $\mathbb{E}[v_i(h_i) | b_i + \varepsilon_i = p]$ .<sup>13</sup> To identify the marginal amount of behavioral hazard (which determines whether mistakes are driving over- or underuse at the margin), we need to know the marginal private benefit since  $\mathbb{E}[\varepsilon_i | b_i + \varepsilon_i = p]$  equals the difference between willingness-to-pay,  $p$ , and the marginal private benefit of treatment. As discussed above, this wedge may be non-zero as the result of any number of biases. But, at best, we typically only have a good sense of the demand curve and the marginal clinical benefit of treatment.

As an illustration of how this could create problems in identifying over- or underuse due to behavioral hazard, consider panel A of Figure 2. In this figure, the demand curve and marginal clinical benefit are sloped in opposite directions. This could occur, for example, if the salience of symptoms (e.g., pain) drives treatment decisions, but clinical treatment benefits tend to be higher when patients are asymptomatic (perhaps because patients are asymptomatic earlier in a disease progression when clinical treatment benefits are the highest). We’d be tempted to say that the marginal patient when prices are high is making a mistake by seeking treatment and the marginal

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<sup>13</sup>In empirical work,  $h_i$  could reflect clinical benefits either gross or net of side effects. For practical purposes, if  $h_i$  is gross of side effects (i.e. does not include them) then the dis-utility from those side effects is included in the wedge between the measured marginal clinical benefit and the marginal private benefit. Other factors that could be a part of the wedge between marginal clinical benefit and marginal private benefit include patients’ intrinsic values for health versus money and patient satisfaction (or lack thereof) from receiving medical care.

Figure 2: The Relationship Between the Demand For Treatment and The Marginal Private/Clinical Benefit of Treatment



patient when prices are low is making a mistake by not seeking treatment. But perhaps  $v_i(h_i)$  is such that, while the patient does mis-react to symptoms, she in fact experiences the greatest utility benefit from treatment when symptoms are salient and the lowest when symptoms are not salient.

Despite such difficulties, there is highly suggestive evidence of under- and overuse due to behavioral hazard, even if there is no empirical proof. Panels B and C in Figure 2 depict the sorts of situations we have in mind. These panels show situations where the demand and marginal clinical benefit curves are known with confidence, while the marginal private benefit curves are unknown (hence the dotted curves in the panels) but believed not to deviate much from the marginal clinical benefit curves. For example, the private benefits of pills treating chronic conditions with few side

effects likely line up closely with monetized clinical benefits. In these cases, despite not knowing the precise marginal private benefit curve, we're fairly confident that conclusions derived from equating this curve with the marginal clinical benefit aren't too misleading.

Much of the evidence on underutilization ( $\varepsilon < 0$ ) comes from (lack of) adherence to prescribed drugs, where the marginal clinical benefit seems to lie above the prices patients face. Panel B of Figure 2 pictures the situation we have in mind. In the case of diabetes, for example, adherence to glucose-controlling drugs is only between 60 and 80% (Rubin, 2005), despite severe health consequences of unmanaged diabetes. One study showed that almost half of diabetic patients did not have their prescriptions filled consistently, despite consistent filling cutting the risk of hospitalization in half (Sokol et al., 2005).<sup>14</sup>

There are also examples of overuse that are hard to reconcile with the standard model, suggesting positive behavioral hazard ( $\varepsilon > 0$ ). Panel C of Figure 2 pictures a situation where we'd be confident of overuse driven by mistakes. While we know of no perfect empirical examples, consider (over)treatment of back pain. Back pain is wide-spread and expensive: it is a leading symptomatic cause of physician visits and cost more than \$25 billion in 1998 (Deyo, Rainville and Kent, 1992; Deyo, Mirza and Martin, 2006; Strine and Hootman, 2007; Luo et al., 2004). Doctors prescribe screenings (e.g., fMRIs) and treatments despite evidence suggesting they are ineffective (Di Iorio, Henley and Doughty, 2000; Jarvik et al., 2003; Lehnert and Bree, 2010; Chou et al., 2009; Sheehan, 2010). The treatment of prostate cancer is another potential example. The disease is rarely fatal and the cancers grow slowly, so the five-year survival rate for those diagnosed is 99.4% (Howlader et al., 2012). Perloth, Goldman and Garber (2010) show that while "watchful waiting" is as effective as more expensive clinical treatments, a large portion of prostate cancer patients pursue these more aggressive options that expose them to risk and don't improve their prognosis.

These documented behaviors (particularly of underuse) likely reflect misutilization due to be-

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<sup>14</sup>Beyond prescription drug non-adherence, patients do not receive recommended care across a wide range of categories, including recommended preventive care (e.g., colonoscopies) and follow-up care (e.g., for asthma management) (McGlynn et al., 2003; Denberg et al., 2005; Ness et al., 2000).

behavioral hazard. First, the magnitudes involved often make the case for unobservable factors less plausible. As an example, reducing copayments from fairly low levels even after an event as salient as a heart attack still produce improvements in adherence: providing medications to prevent future heart attacks for free (instead of at roughly a \$10-\$25 copayment) increased adherence by about 5 percentage points (relative to a base of 35-50 percent), and this increase was associated with a reduced rate of subsequent major vascular events (Choudhry et al., 2011).

Second, while there is plenty of evidence of heterogeneous treatment benefits, there is less evidence that people self sort in the manner we'd expect under a model where willingness to pay is increasing in treatment benefits. For example, Goldman, Joyce and Karaca-Mandic (2006) look at the impact of a small (\$10) increase in copayments for cholesterol-lowering medications. They find that it drives similar reductions in use of those medications among those with high risk (and thus high health benefits) as those with much lower risk. One possibility is that willingness-to-pay does not increase with treatment benefits because some unobserved factor (let's call it "sick tolerance") tends to correlate with willingness-to-pay and treatment benefits, making the marginal private benefit curve look quite different from the marginal clinical benefit curve. But it strikes us that a more natural hypothesis is that some people are making mistakes.

How consumers respond to the structure of health incentives further builds the case that the demand for treatment is richer than predicted by the standard model.

### **3.1.2 Inconsistent Responses to Price Levers**

The degree of behavioral hazard is not only a function of the disease and treatment. Evidence suggests that insurees respond in inconsistent ways (from the perspective of a neo-classical model) to different price levers:  $\varepsilon$  is influenced by levers that make up the price  $p$ .

Insurees appear to overreact to "spot prices" (out-of-pocket expenses tied to care) relative to expected end-of-year prices (how care influences out-of-pocket expenses over the course of the insurance cycle). Suppose the deductible is \$X and there is no cost sharing beyond the deductible. Also, suppose (for sake of example) that the insuree will for sure exhaust the deductible by the

end of the year. Then no matter what the insuree will pay  $\$X$  on care over the course of the year. The evidence says, however, that the insuree is more reluctant to seek care towards the beginning of the year when he has not yet exhausted the deductible than towards the end when he has (Einav, Finkelstein and Schrimpf, 2015; Dalton, Gowrisankaran and Town, 2015; Abaluck, Gruber and Swanson, 2015; Aron-Dine et al., 2015; Brot-Goldberg et al., 2017). It is as if he does not recognize that  $\$X$  is in expectation a sunk cost.<sup>15</sup>

Such differential reactions imply that the shape of a non-linear insurance schedule influences how much care insurees consume, fixing how much care a fully rational insuree would consume under different plans. For example, in high-deductible health plans spot prices decrease over the course of an insurance cycle, so such plans reduce spending by more when insurees overreact to spot prices. This spending reduction may have adverse and undesirable consequences for health, as discussed below.

Reactions to price levers may interact with nudges that influence insurees' understanding of health insurance, as insurees seem to lack a basic understanding of many plan features (e.g., Loewenstein et al. 2013).

### 3.1.3 Nudge Responses

Evidence also suggests that insurees respond to nudges (Thaler and Sunstein, 2009), where following Mullainathan, Schwartzstein and Congdon (2012) we conceptualize nudges as levers that would not influence consumer demand in the neo-classical model: nudges  $n$  influence decisions through impacting  $\varepsilon$  but not  $b$  or  $p$ . There is ample evidence that interventions targeting patient communication (not just by influencing what information is conveyed but also how it is conveyed) can produce substantial changes in adherence (e.g., Cutrona et al. 2010), as can text message reminders or simplifications of dosage schedules (Schedlbauer, Davies and Fahey, 2010; Schroeder,

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<sup>15</sup>Explanations for the overreaction to spot prices include myopia (Dalton, Gowrisankaran and Town, 2015), "schmeduling" (Liebman and Zeckhauser, 2004), limited information (Handel and Kolstad, 2015b), and liquidity constraints. There are contexts where the last explanation is unlikely to be at play because consumers overreact to spot prices even when they are relatively well off and have easy access to credit (Brot-Goldberg et al., 2017). Interestingly, insurees appear even more responsive to copays than out-of-pocket-equivalent deductibles (Stockley, 2016).

Fahey and Ebrahim, 2004; Strandbygaard, Thomsen and Backer, 2010; Long et al., 2012; Lafeber et al., 2017; Patel et al., 2015).<sup>16</sup>

But which combination of nudges work to improve treatment outcomes (and when) is a complex and open question. The REMIND trial—a large-scale randomized trial evaluating the adherence effects of low-cost medication reminder devices, including a digital timer cap and a pill-bottle strip with toggles—did not find improvements in adherence (Choudhry et al., 2017). The Heart-Strong intervention, which involved a mix of nudge and non-nudge interventions such as providing electronic pill bottles, lottery financial incentives, and social support for survivors of acute myocardial infarction, also did not boost adherence (Volpp et al., 2017). Right now, it seems that the most reliable lever that influences outcomes is a traditional one: prices. We next take up the question of how behavioral economics influences how we think about basic health-insurance tradeoffs involving prices.

### 3.2 Re-Thinking Basic Health Insurance Tradeoffs

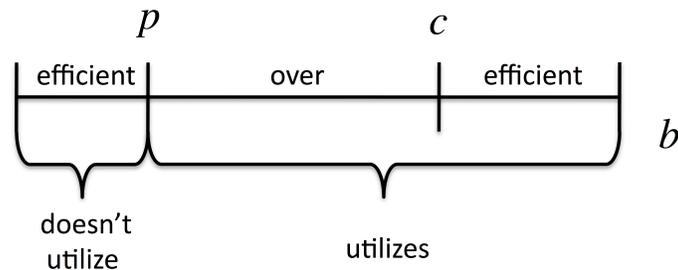
The neo-classical model identifies a fundamental moral hazard tradeoff: lowering the price of care increases insurance value but leads to overutilization (Arrow, 1963; Pauly, 1968; Zeckhauser, 1970; Cutler and Zeckhauser, 2000). To illustrate, suppose a person may get a headache of severity  $s$ , where  $s$  is drawn from some distribution and is private information. Treatment provides benefit  $b(s)$  ( $b'(\cdot) > 0$ ) and costs society  $c$ . It is socially efficient for the person to get treated only if the headache is sufficiently severe that  $b(s)$  exceeds  $c$ . But providing insurance means that the price for treatment, which for simplicity we will equate with a copay in this section, is below cost,  $p < c$ . So if a person is rationally deciding whether to get treated then he seeks treatment whenever  $b(s) > p$ , generating situations where the person chooses to treat headaches (e.g., by going to the doctor) in situations where it is socially inefficient for him to do so.

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<sup>16</sup>There are also nudges that effectively increase preventive care like vaccinations. Milkman et al. (2011), for example, find that a “planning prompt” that encouraged adults to plan a date and time to get a flu shot boosted the number of adults who obtained a flu shot by 4.2 percentage points. The nudge perhaps operated by reducing forgetfulness. Chapman et al. (2010) find that automatically scheduling individuals for vaccination appointments (which they could opt out of) likewise increased vaccination rates.

More generally, suppose as in Figure 3 that treatment benefits  $b$  are distributed on a line, where sometimes benefits exceed and other times fall below the social cost of treatment  $c$ . Then whenever the treatment is insured ( $p < c$ ) there is overuse in the region where benefits exceed copays but fall below costs ( $b \in (p, c)$ ). According to the moral hazard model, overutilization is the big concern—and overutilization is created by insurance.

Figure 3: Model with Only Moral Hazard



Source: Baicker, Mullainathan and Schwartzstein (2015)

### 3.2.1 Re-interpreting the Benefits of Health Insurance

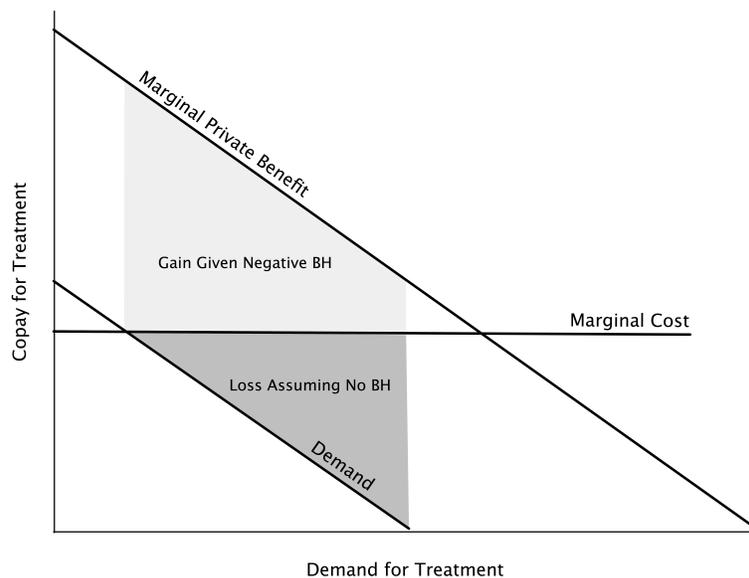
Behavioral hazard modifies this analysis. Misutilization is not only driven by insurance, but also by mistakes. As discussed above, underutilization—not just overutilization—is a concern. When behavioral hazard is negative ( $\varepsilon < 0$ ), for example, a person inefficiently fails to get treated when  $b > c$  but  $b + \varepsilon < p$ .

In natural cases, then, behavioral hazard reverses the risk-protection/moral hazard tradeoff. Figure 4 compares the welfare impact of reducing the copay (price) from  $p = c$  to 0 when there is no behavioral hazard to when there is significantly negative behavioral hazard, under the assumption of local risk neutrality to isolate the moral/behavioral hazard impact. The dark gray area represents the standard deadweight loss triangle—the moral hazard cost of insurance. This area is positive because getting treated only when the price is below marginal cost signals that a person's willingness to pay must be below this cost.

The standard approach makes an often implicit assumption: analagous to identifying welfare

curves in treatment choices (described above), we can equate willingness to pay for treatment with the true marginal benefit of treatment. That is, being marginal at a copay signals that  $b = p$ . Behavioral hazard drives a wedge between these objects. Being marginal at a copay signals that  $b = p + \varepsilon$ . The figure illustrates the case where all people have a propensity to underuse because of negative behavioral hazard and share the same  $\varepsilon < 0$ . In this case, the marginal benefit curve lies above the demand curve and the vertical difference equals  $\varepsilon$ . When the magnitude of negative behavioral hazard ( $|\varepsilon|$ ) is sufficiently large, the marginal benefit of treatment outweighs the marginal cost even when the copay equals 0. In this case, reducing the copay to 0 no longer generates a welfare cost of increased utilization but a welfare benefit equal to the light gray area in the figure.

Figure 4: Welfare Impact of a Treatment Price Change: (Negative) Behavioral Hazard vs. Moral Hazard Alone



Source: Baicker, Mullainathan and Schwartzstein (2015)

Notes: This figure considers the welfare impact of reducing the price of treatment to zero when there is only moral hazard to when there is also negative behavioral hazard. It is drawn for the case where all people share the same  $\varepsilon < 0$ .

### 3.2.2 Re-Interpreting the Elasticity of Demand for Treatment

Behavioral hazard also changes how we empirically measure the benefits and costs of insurance. Define  $m(p)$  to be an individual's forecasted demand for care at a given copay: it equals 1 if and only if  $b + \varepsilon > p$ . Aggregate demand then equals  $M(p) = \mathbb{E}[m(p)]$ . The extent of moral hazard is typically calibrated by the price sensitivity of demand for medical care (either  $M'(p)$  or the elasticity of demand). As can be seen in the figure, absent behavioral hazard the welfare cost of insurance (the dark grey area) is greater the flatter the demand curve: more elastic demand means a greater moral hazard cost of insurance.

There is much work measuring the elasticity of demand for medical care for the purpose of calibrating the degree of moral hazard (e.g., Feldstein (1973); Manning et al. (1987); Feldman and Dowd (1991); Newhouse (1993)). Perhaps the most famous example is work on the RAND Health Insurance Experiment, which randomly assigned insurees to different degrees of cost sharing and found a demand elasticity of roughly -.2. Recent work (e.g., Aron-Dine, Einav and Finkelstein (2013); Finkelstein (2014)) has made a lot of progress developing ways to more accurately measure how changes in cost sharing impact medical-care spending, especially taking into account the non-linear nature of insurance coverage. But for the most part it maintains the assumption that the price-sensitivity of demand for medical care meaningfully captures the degree of moral hazard.

The presence of behavioral hazard complicates this analysis. This is because the care that is encouraged when co-pays are reduced may in fact be high value. Indeed, the light grey area of the figure is greater the flatter is demand: with sufficiently negative behavioral hazard, up to a point more elastic demand now means a greater *benefit* of insurance.

As an empirical matter, changes in cost-sharing (from small levels) impact the demand for both high *and* low-value care (Lohr et al., 1986; Goldman, Joyce and Karaca-Mandic, 2006; Chandra, Gruber and McKnight, 2010; Brot-Goldberg et al., 2017). For a recent example, Brot-Goldberg et al. (2017) examine data from a large self-insured firm that switched from a plan with free health care to a high deductible plan and find that insurees responded by not only reducing the quantity of potentially wasteful care (identified following Schwartz et al. 2014), but also by meaningfully

reducing the quantity of high value care (e.g., drugs for diabetes, cholesterol, depression etc.). Moreover, spending reductions were almost entirely due to quantity reductions and not to price shopping or substitution across procedures by insurees. Equating the price-sensitivity of demand for medical care with the degree of moral hazard is potentially quite misleading.

### **3.2.3 Re-Interpreting Health Impacts of Price Changes**

To examine the welfare impact of cost-sharing changes, it is beneficial to "get under the hood" and examine health impacts of discouraging care by increasing prices. One approach is to directly measure health markers like blood pressure, adverse health events (e.g., heart attacks), mortality, etc. This is an approach taken by, e.g., Choudhry et al. (2011).<sup>17</sup> Another approach, which is less direct but sometimes more empirically feasible, is to measure how a decrease in medical care (e.g., prescription drug use) in response to higher cost sharing (e.g., higher drug copays) results in "offsetting" increases in other forms of medical care (e.g., hospital utilization). Using a quasi-experimental design of the effects of increases in copayments for prescription drugs and physician visits among retirees in California, Chandra, Gruber, and McKnight (2010) show that there are significant offsetting increases in hospital utilization. It's possible that the retirees are rationally trading off the risk of hospitalization against copays and side effects, but in interpreting the findings it's useful to keep in mind that much of the cost of hospitalization is large and uninsurable (e.g., many procedures in the hospital are painful and come with a significant time cost).

As a result, incorporating behavioral hazard provides a foundation for value-based insurance design (Chernew, Rosen and Fendrick, 2007), specifying lower cost-sharing for higher value care. To take a very simple example, suppose the demand curve for a given (disease, treatment) combination slopes down only because of behavioral hazard ( $\text{Var}(b) = 0, \text{Var}(\varepsilon) > 0$ ) and insurees are approximately risk neutral. Then the welfare impact of a co-pay change can be identified by examining the average value of the treatment  $b$ . In this case, it is optimal to set the copay below

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<sup>17</sup>Sommers, Gawande and Baicker (2017) provide a summary of the evidence on how health insurance coverage impacts health.

cost (perhaps even subsidizing treatment) if and only if  $b > c$ .<sup>18</sup>

### 3.3 Implications for Insurance Markets and Policy

The analysis above suggests that socially efficient health insurance contracts should be designed to help counteract biases.<sup>19</sup> Will equilibrium health insurance contracts be designed with this in mind? Is there room for behaviorally-minded welfare-improving government intervention?<sup>20</sup>

We derive the equilibrium insurance contract in a competitive market. This contract may differ from the optimal contract because people may not fully understand how they are biased and misforecast their demand for treatment. Formally, define  $\hat{m}(p)$  to be an individual's forecasted demand for care at a given copay: it equals 1 if and only if  $b + \hat{\varepsilon} > p$ , where  $\hat{\varepsilon}$  represents the forecasted degree of behavioral hazard. At the time of contracting, the insuree may not appreciate that she will undervalue the need to take a chronic disease medication or that she will seek out any treatment for back pain. Define forecasted aggregate demand to equal  $\hat{M}(p) = \mathbb{E}[\hat{m}(p)]$ . In common with much of the behavioral literature, we will highlight two extreme cases: the case where the insuree perfectly understands her biases and the case where she thinks she is unbiased at the time of contracting. Formally, the agent is said to be *sophisticated* when  $\hat{\varepsilon} = \varepsilon$  (e.g., correctly forecasting that she will act as if she undervalues the need to take a chronic disease medication) and to be *naive* when  $\hat{\varepsilon} = 0$  (e.g., incorrectly thinking she will act as if she properly values the need to take a chronic disease medication).<sup>21</sup>

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<sup>18</sup>Value-based insurance designs are attracting increasing attention in policy circles. For example, the Centers for Medicare and Medicaid Services are testing such designs, as is the Department of Defense (Frakt, 2017).

<sup>19</sup>Much of this section's content and language previously appeared in Baicker, Mullainathan and Schwartzstein (2012)—a working paper version of Baicker, Mullainathan and Schwartzstein (2015).

<sup>20</sup>This analysis follows much of the existing theoretical literature (e.g., as implicit in Blomqvist 1997) and formally models a situation where insurers compete directly to attract potential insurees. By closely following this work, the analysis isolates the market failure resulting from behavioral hazard, holding other institutional features constant.

<sup>21</sup>There is another potential form of naivete, namely that insurees misperceive treatment benefits at the time of contracting, not just at the time of making a treatment decision (i.e., at the time of contracting, they misforecast the benefit of getting treated as  $b + \varepsilon$ ). It would be natural to assume this form of naivete if decision errors are the result of incorrect beliefs about treatment benefits, for example, but not if these errors are the result of biases such as procrastination. We abstract from this form of naivete to limit the number of cases considered. However, we note that it is particularly easy to characterize the equilibrium outcome given this form of naivete: it is just the solution to the planner's problem if the planner mistakenly perceives treatment benefits as equaling  $\hat{b} = b + \varepsilon$ .

In equilibrium, the market will supply an insurance plan to maximize the agent’s *perceived* expected utility subject to zero profit constraint.<sup>22</sup> The agent’s perceived expected utility can differ from her actual utility because she may misforecast her demand for treatment.

Since the optimal contract maximizes perceived expected utility subject to a zero profit constraint, it is immediate that the optimal and equilibrium contract coincide when the agent is sophisticated. In the more general case, the agent may misforecast demand and consequently view the tradeoff between a higher co-pay and a lower premium as being more or less favorable than it actually is. Overforecasting the degree to which the premium should go down reduces the apparent desirability of raising the co-pay; underforecasting raises the apparent desirability.

### 3.3.1 Market Failures Arising from Consumers’ Naivete

The equilibrium co-pay differs from the optimal co-pay because the agent misforecasts demand: there is a market failure resulting from lack of sophistication. To gain more intuition for how this works, consider the simple case of a risk-neutral naive agent. In this case, the optimal co-pay formula reduces to

$$p^B = c + \varepsilon(p^B), \tag{10}$$

where  $\varepsilon(p^B)$  is the degree of behavioral hazard of the marginal insuree given copay  $p^B$ . At the optimal co-pay, the marginal agent fully internalizes her “internality” (the difference between  $p$  and  $c$  acts as a Pigouvian tax set at the level of the marginal internality  $\varepsilon(p)$ ).<sup>23</sup>

On the other hand, Baicker, Mullainathan and Schwartzstein (2012) show that the equilibrium

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<sup>22</sup>As is well known, the solution to this problem will coincide with the outcome when insurers maximize profits subject to an “individual rationality” constraint for the representative agent, where the consumer’s outside option is such that the solution to this problem yields zero profits. In fact, the logic of the equilibrium co-pay holds for *any* outside option, so the degree of market power does not change the logic of how co-pays will be set in equilibrium.

<sup>23</sup>Since the optimal co-pay in this case acts as a Pigouvian tax to get the agent to internalize his internality, it is tempting to think that the analysis would be the same if we were to think of  $\varepsilon$  as an externality rather than an internality. However, there are important differences. If  $\varepsilon$  were an externality then market forces alone would not correct the problem (Coasian bargaining seems unlikely in this setting)—government intervention would be necessary. However, when people are sophisticated, market forces may correct an internality. Likewise, even when people are naive, market forces can lead to an equilibrium in which agents partially internalize their internality, as we will soon see.

co-pay in this case,  $p^E$ , is instead set to take advantage of the difference between actual and predicted demand: the larger this difference, the greater the co-pay.<sup>24</sup> To illustrate how the equilibrium copay differs from the optimal copay, suppose insurees are inattentive and forget to get treated with some probability that is independent of decision benefits and costs. The optimal copay does not depend on the forgetting probability because this probability does not influence decisions at the margin. Yet, at the same time, forgetfulness leads agents to overforecast their usage and, in equilibrium, profit maximizing firms will have an incentive to lower the copay (and create “fictitious surplus”) in response to this bias.

### 3.3.2 Insurers’ failure to provide nudges that benefit insurees may flow from insurees’ naivete about the impact of such nudges

Now suppose insurers are also able to use nudges. Define  $\hat{m}_n(p)$  as the individual’s forecasted demand for care at a given price conditional on nudge  $n$ :  $\hat{m}_n(p)$  equals 1 if and only if  $b + \hat{\varepsilon}_n > p$ . Let  $\hat{M}_n(p) \equiv \mathbb{E}[\hat{m}_n(p)]$  equal forecasted aggregate demand given a nudge. For a sophisticated consumer,  $\hat{\varepsilon}_n = \varepsilon_n$  for all  $n$ : sophisticates completely understand how nudges will affect their decisions. For a naive consumer,  $\hat{\varepsilon}_n = 0$  for all  $n$ : naifs think their decisions will be independent of nudges. Naifs do not appreciate that reminders and educational programs will improve adherence, or that small hassle factors will greatly influence whether they seek treatment.

We assume that nudges can be contracted over. If the representative agent is sophisticated it is again immediate that the equilibrium insurance contract will be efficient. In particular, nudges will be supplied optimally. Matters are different if the agent is naive. In this case,  $\hat{m}_n$  is independent of  $n$ , so nudges will only affect perceived expected utility insofar as they influence the size of the

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<sup>24</sup>Under regularity conditions, Baicker, Mullainathan and Schwartzstein (2012) show that  $p^E$  satisfies

$$p^E = c + \frac{M(p^E) - \hat{M}(p^E)}{|M'(p^E)|}. \quad (11)$$

$p^E$  deviates from  $c$  for reasons analagous to why profit-maximizing firms may charge high up-front fees and below-cost usage prices for “investment goods” when consumers are partially naive about their self-control problems (DellaVigna and Malmendier, 2004). In this way, our model may help explain why the insurance plans we see in the world appear “too generous” (too low co-pays and deductibles) relative to simulated optimal plans (Cutler and Zeckhauser, 2000).

premium through the zero profit constraint. Fixing the co-pay, the nudge that maximizes perceived expected utility subject to the zero profit constraint will be the one that minimizes insurer costs. When the equilibrium co-pay is lower than cost  $c$ , this means the equilibrium nudge will (weakly) discourage care relative to the default nudge. This is independent of the initial bias: when nudges are available, equilibrium insurance contracts may exacerbate rather than help counteract biases.

Matters are different when insurers' bottom line depends indirectly on whether agents are treated, perhaps because a failure to get treated will lead to greater expenses within the horizon of the insurer. For example, it may be costly to the insurer if an insuree does not get a flu shot. The equilibrium nudge may encourage care in this situation even when agents are naive, as such a nudge may improve the insurer's bottom line.

These results suggest that competitive forces do not lead to efficient equilibrium insurance contracts when insurees are naive about their biases, but that the insurer will have an incentive to counteract biases when this saves *the insurer* money. For example, Starc and Town (2016) find that Medicare prescription drug coverage plans spend more on drugs when they cover all medical expenses than when they are only responsible for prescription drug spending, and this spending is concentrated on drugs that produce offsets. This is consistent with such plans having more of an incentive to counteract behavioral hazard.

## **4 Future Directions for Behavioral Health Economics**

There are many interesting topics for future research in behavioral health economics. To conclude, we highlight some of these topics. We follow the structure of this chapter and divide our discussion into topics related to insurance choices and those related to treatment choices.

### **4.1 Future Work on Health-Insurance Choices**

While there has been much research showing that consumers have a difficult time choosing insurance options in both active and passive settings, there is much to be done to better understand why

and to investigate policies to improve these choices. Policies that should be studied further include:

- Providing information to consumers. What forms of information are effective and what is the upper bound for effectiveness in this domain?
- Impact of consumer education / literacy. How do we educate consumers to make better choices?
- Active choice. When consumers have a default option, is forced active choice a welfare-enhancing policy?
- Targeted/smart defaults. What is the impact of targeted/smart defaults on choices? What are the impacts of setting such defaults on competitive markets? How can targeted defaults be best designed to fulfill social objectives?
- Curated choice sets. What are welfare-maximizing curated choice sets in competitive markets?

To think about such policy questions, it is important to more broadly understand how insurers respond to consumer biases. While we mentioned some findings on this topic above, there is room for much more empirical and theoretical work speaking to whether, how, and when insurers set prices or design products to take advantage of consumer mistakes.

An additional area for future research is to investigate the role of non-standard risk preferences and systematic biases in health-insurance choices. As discussed in Section 2, empirical analyses typically focus on classical expected utility models, with minor modifications, or reduced-form frameworks that nest a slew of models. Future work in this area could estimate models that incorporate reference-dependent preferences (e.g., Kőszegi and Rabin (2007)) or context-dependent choices arising from salience, focusing, and relative thinking (e.g., Bordalo, Gennaioli and Shleifer (2012); Koszegi and Szeidl (2013); and Bushong, Rabin and Schwartzstein (2018)).

A related topic concerns the degree to which consumers make consistent choices across domains (from the perspective of given models of risk preferences). Einav et al. (2012) studies

whether consumers make consistent choices, in terms of ordering of riskiness, across multiple benefit choices at Alcoa. Within one private firm, Barseghyan, Molinari and Teitelbaum (2016) perform a similar study of consumers making multiple non-health insurance choices across the domains of property and auto insurance. Investigating consistency across health-insurance choices (and across other related choices) could provide insights that are useful for positive and normative analyses.

## **4.2 Future Work on Health-Treatment Choices**

In our earlier discussion of health-treatment choices, we abstracted from several important issues by analyzing a single “choice to treat”. Unpacking what we mean by a treatment choice reveals many more areas to apply insights from behavioral economics.

First, before people are treated, they often must be tested. If people rationally respond to information and hold classical expected utility preferences, then testing must be valuable because it provides potentially useful information. While we’ve mostly focused this chapter on mistakes rather than non-standard preferences, anxiety or a desire to remain optimistic (e.g., Kőszegi (2003) and Oster, Shoulson and Dorsey (2013)) may lead people to avoid testing—and perhaps be made better off as a result. More relevant to discussions in this chapter, mistakes at the treatment stage may create small or even negative returns at the testing stage, resulting in larger benefits to counteracting behavioral hazard (Baicker, Mullainathan and Schwartzstein, 2015). For example, recent large scale clinical trials indicate that Prostate Specific Antigen (PSA) screening for prostate cancer has, at best, a small effect in reducing mortality, and that the risks likely outweigh the benefits (Andriole et al., 2009; Djulbegovic et al., 2010). A natural question is whether such a conclusion would be reversed if more patients diagnosed with prostate cancer were nudged or incentivized to pursue “watchful waiting”.

Second, treatment choices are often made in consultation with a doctor who may also be subject to behavioral biases. Chandra et al. (2012) review behavioral influences in clinical decisions. One example is the availability heuristic (Tversky and Kahneman (1973))—the idea that people predict

the frequency of an event by the ease with which it comes to mind. This suggests that a physician who has just seen a patient with influenza may be more likely to make the diagnosis of influenza for the next patient. Choudhry et al. (2006) found evidence for availability influencing clinical decisions. They showed that physicians who treated a patient with Warfarin (a blood-thinning drug with the risk of bleeding) and saw that patient experience an adverse bleeding event were 21 percent less likely to prescribe Warfarin to other patients for which Warfarin is indicated, even 90 days after the adverse event. Physicians are humans too and are subject to the same influences (e.g., of framing, status-quo bias, and messaging) that systematically influence other humans. A topic for future work is to better understand the interaction between physician and patient biases.

Third, if the treatment is medication, people have to not only fill their prescriptions but also take their pills. There is a large literature on patient adherence, reviewed by Osterberg and Blaschke (2005), that we briefly discussed. While the evidence suggests that making high-value drugs free will promote people filling prescriptions and taking their pills, many people will not be adherent even if they have their pills on hand. For example, they may forget to take them. Much research is exploring ways to boost adherence, such as the REMIND trial discussed above. Improving adherence should increase the benefits of counteracting behavioral hazard in decisions to fill prescriptions.

Fourth, the benefits of treatment will interact with “lifestyle behaviors”, for example involving diet, exercise, and smoking. Loewenstein, John and Volpp (2012) provide a nice review of behaviorally-informed attempts to help people help themselves. Many of these attempts to date take the form of financial incentives, but framed or structured in a way to have a reasonable bang-for-buck given the errors people make. As a recent illustration, Halpern et al. (2015) conduct a randomized trial of financial-incentive programs for smoking cessation among CVS Caremark employees and find that individual rewards of \$800 comes close to tripling the rate of cessation. Paying careful attention to the structure of incentives (e.g., paying separate and salient rewards rather than incorporating them into insurance-premium adjustments) seems particularly important in these cases because the people we want to target have revealed that they do not respond to big

(but perhaps not salient) incentives to change their behaviors (Volpp et al., 2011).

Future research could use a behavioral lens to further unpack the dimensions of treatment decisions and explore interactions between them.

Finally, a theme throughout this chapter is that we're often more confident that people are making *some* mistake in their health-insurance or health-treatment choices than *why* they are making a mistake in these choices. We believe the explosion of research described above convincingly points to pitfalls in analyzing demand curves for insurance or medical care while maintaining the assumption that choices perfectly reveal preferences. And we believe it shows that researchers are able to make progress in studying these decisions (and difficulties in making them) without understanding the precise mechanisms behind consumer mistakes. That said, parallel work described in other chapters of this Handbook suggest large future gains to understanding the "whys" behind poor insurance and treatment choices.

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