THE HAMILTON PROJECT

DISCUSSION PAPER 2015-08 | OCTOBER 2015

Getting the Most from Marketplaces: Smart Policies on Health Insurance Choice

Ben Handel and Jonathan Kolstad

MISSION STATEMENT

The Hamilton Project seeks to advance America's promise of opportunity, prosperity, and growth.

We believe that today's increasingly competitive global economy demands public policy ideas commensurate with the challenges of the 21st Century. The Project's economic strategy reflects a judgment that long-term prosperity is best achieved by fostering economic growth and broad participation in that growth, by enhancing individual economic security, and by embracing a role for effective government in making needed public investments.

Our strategy calls for combining public investment, a secure social safety net, and fiscal discipline. In that framework, the Project puts forward innovative proposals from leading economic thinkers — based on credible evidence and experience, not ideology or doctrine — to introduce new and effective policy options into the national debate.

The Project is named after Alexander Hamilton, the nation's first Treasury Secretary, who laid the foundation for the modern American economy. Hamilton stood for sound fiscal policy, believed that broad-based opportunity for advancement would drive American economic growth, and recognized that "prudent aids and encouragements on the part of government" are necessary to enhance and guide market forces. The guiding principles of the Project remain consistent with these views.

THE HAMILTON PROJECT

THE HAMILTON PROJECT

Getting the Most from Marketplaces: Smart Policies on Health Insurance Choice

Ben Handel
Economics Department, University of California, Berkeley

Jonathan Kolstad
Haas School of Business, University of California, Berkeley

OCTOBER 2015

BROOKINGS

Abstract

Recent reforms to regulated U.S. health insurance markets—such as the Patient Protection and Affordable Care Act (ACA) of 2010 state exchanges and Medicare Part D—are motivated by a presumption that well-informed and active consumers will play a key role in supporting vigorous insurer competition. However, recent evidence suggests that it is difficult for many consumers to make fully informed and effective choices in these markets. The poor choices that result can lead to large financial losses for consumers, as well as for the federal and state governments who subsidize their insurance purchases. These losses manifest both from consumers choosing poor plans given those offered in the market and from the less-efficient offerings that result from less-intense insurer competition.

In this paper we propose two policies intended to improve the functioning of these markets by improving consumer choices. First, we propose that market regulators adopt and promote targeted consumer search tools that personalize choice framing and recommendations based on an individual's specific characteristics. These tools will guide consumers toward plans that they are best suited for, while giving them the flexibility to clearly assess products on dimensions that are important to them. Second, we propose a set of more proactive smart default policies designed to improve the allocation of insurance plans when the regulator has substantial confidence that a consumer is enrolled in a poor plan match. Under our proposal, when the regulator has enough information to do so, it can "default," or opt consumers enrolled in existing plans into different existing plans during open enrollment, when it is clear that such a switch presents an unambiguous and substantial increase in value. These smart default policies are stronger when regulators possess more consumer-specific information, and allow for consumers to actively choose any plan in the market if they wish. We lay out in detail the key components of each policy, discuss contextual factors that make each more or less appropriate, and note some potential limitations.

Table of Contents

Chapter 1. Introduction

Both of the most significant recent reforms to U.S. health care—the Patient Protection and Affordable Care Act (ACA) of 2010 and the Medicare Prescription Drug, Improvement, and Modernization Act of 2003 (known as the Medicare Modernization Act) before it—rely heavily on private provision of health insurance purchased by individuals, with some form of subsidy for many participants. A key assumption on which these reforms are founded is that active and well-informed consumers choosing health insurance plans from a large menu of options each year will support vigorous competition among insurers. However, recent evidence suggests that, in the current environment, it is difficult for those purchasing insurance to make fully informed and effective choices among the many plans offered by insurers. Consumers, state governments, and the federal government stand to lose when individuals' impaired decisions hinder market forces and limit the role of competition in lowering prices and improving quality. Estimates from existing research suggest that these losses are substantial and manifest in the form of higher health-care costs for consumers and higher government outlays through greater public support for subsidized access to health-care coverage.

In this proposal, we recommend a simple set of changes to the way in which insurance policies are purchased that can dramatically enhance consumer welfare, create incentives for innovation in the health insurance market, and lower government costs associated with providing subsidized coverage. First, we recommend that the Centers for Medicare & Medicaid Services (CMS) and state health exchange operators, which we refer to as the regulator, adopt and promote a narrower and more-targeted consumer search tool than is currently used to compare health insurance plans offered through Medicare or the health insurance exchanges. Such a tool would be forward-looking and personalized. We propose a number of design features of such a tool that would enable consumers to easily compare products in the market on the key dimensions that are important to them. To the extent that it helps avoid product obfuscation, we recommend that the regulator standardize financial elements of insurance products so that consumers do not need to learn unnecessary jargon describing the various features of health insurance plans or to perform complex calculations. On product dimensions where differences across insurers are essential for creating discernible plans, such as the network of providers offered, the regulator should develop and clearly present metrics for consumers to actually assess the value of those product attributes. While this recommendation seems simple and straightforward, it is still not effectively implemented in most insurance exchanges so selecting an insurance plan remains a complex endeavor.

Second, we propose a set of more proactive—or smart default—policies designed to improve the allocation of insurance plans when the regulator has substantial confidence that a consumer is enrolled in a poor plan match. These smart default policies rely on (i) consumer-specific information and (ii) a trustworthy underlying model of when choice mistakes are especially large in magnitude. Under our proposal, when the regulator has enough information to do so, it can default or opt consumers enrolled in existing plans into different existing plans during open enrollment, when it is clear that such a switch presents a clear and substantial increase in value. Specifically, a default is the plan that an individual is automatically enrolled in should she take no action to switch plans. But the individual can switch to a different plan—for example, a plan in which she was previously enrolled—by making an active choice. We define and discuss the threshold for what constitutes a clear and substantial increase in value according to (i) the expected financial benefit, (ii) the worst-case financial outcome from the switch, and (iii) the condition that provider continuity is maintained for the consumer. We discuss the potential for this policy to enhance both the value that consumers obtain from the market, and the public sector savings resulting from consumers switching into cheaper plans that require fewer outlays or subsidies. We also discuss the trade-offs inherent in more-aggressive choice architecture policies like smart defaults.

While some of the policies we recommend should be implemented in all insurance exchanges, the more-aggressive choice architecture policies we suggest may be appropriate only for select exchanges with specific characteristics. We close with a discussion of when the weaker choice policies we propose (targeted information provision and recommendations) are preferable to the stronger policies (smart defaults).

Chapter 2. Challenge and Evidence: Consumer Choice in Health Insurance

There is a large existing literature documenting choice errors that, first, are costly to consumers, exchange operators, and taxpayers; and, second, could be addressed by the kind of personalized decision support we propose. Summaries of the most relevant papers are presented in table 1. We now discuss some of these studies to provide a sense of the types of mistakes consumers make and the corresponding financial implications. These papers are relevant both to the personalized recommendation policies described in this section and to the smart default policies described in the next section.

TABLE 1.

Literature on Health Insurance Choices

Studies of Consumer Choice in Health Insurance Markets

Study	Market	Key Results
Handel (2013)	Large-employer	Investigates inertia in health plan choice, and shows that in the large employer setting studied, consumers leave approximately $2,000 on the table due to inertia, on average. Many consumers remain in dominated plans, where they lose a substantial amount of money for sure in inertial choice environments. Handel finds that, if consumer inertia is reduced, adverse selection would likely increase in a marketplace with no insurer risk-adjustment transfers.
Bhargava, Loewenstein, and Sydnor (2015)	Large-employer	Studies employees who actively choose from 48 plans with a lot of flexibility to build their own plan on financial dimensions. Employees frequently choose dominated options, resulting in an average excess spending of 42 percent of annual premium. Choices do not improve over time. Lab intervention ties results to fundamental lack of understanding of insurance products.
Handel and Kolstad (2015)	Large-employer	Studies role of limited information in plan choice by investigating consumer choice between plans at large-employer using claims, choice, and survey data related to consumer information about plan options. Consumers lack information about plan provider networks, financial characteristics, and hassle costs that can cause them to leave thousands of dollars on table in choice.
Strombom, Buchmueller, and Feldstein (2002)	Large-employer	Documents evidence of inertia in a large-employer setting, related to (i) whether choices are active or passive and (ii) whether consumers have active ongoing medical care (which makes them less likely to switch).
Abaluck and Gruber (2013)	Medicare Part D	Documents money left on table in Medicare Part D prescription drug plan choices over time. There is limited consumer learning; consumer forgone savings increase over time, in large part because of changes to plan designs over time combined with consumer inertia.

Studies of Consumer Choice in Health Insurance Markets (continued)

Study	Market	Key Results
Abaluck and Gruber (2011)	Medicare Part D	Documents money left on table in Medicare Part D prescription drug plan choices. Elders place higher weight on premiums than on other financial characteristics, and place very little weight on aspects of plans that reduce financial risk. Consumers would have been 27 percent better off if all chose rationally, and market remained as observed.
Ho, Hogan, and Scott Morton (2015)	Medicare Part D	Documents money left on table both in active choices and from inertia in Medicare Part D market in New Jersey. Studies supply-side responses to consumer inertia, and shows that reducing inertia could have substantial impact on competition, and markedly reduce premiums, leading to both increased consumer welfare and government savings.
Kling et al. (2012)	Medicare Part D	Studies elders making Medicare Part D plan choices. Performs information intervention where elders are given targeted information about which plans might be best for them. Increases switching rate for elders, and improves their plan choices.
Ericson (2014)	Medicare Part D	Documents persistence in consumer choice in Medicare Part D market, and pricing patterns consistent with “invest then harvest” pricing where insurers take advantage of consumer inertia in pricing.
Heiss, McFadden, and Winter (2010)	Medicare Part D	Provides evidence on choice in Medicare Part D, documenting consumer attitudes and money left on table in initial, active Medicare Part D choices.
Ketcham et al. (2012)	Medicare Part D	Studies specific behavior of Medicare Part D enrollees over time in 2006 and 2007. Within sample, evidence that people made substantially better choices in 2007 than 2006, indicating consumer learning about product value over time.
Ketcham, Lucarelli, and Powers (2015)	Medicare Part D	Shows that 50 percent of consumers were not enrolled in their 2006 drug plans by 2010, and that switchers gained better plan value. Having more choices is correlated with increased switching rates, implying choice overload may not be a problem on the margin in Medicare Part D.
Polyakova (2014)	Medicare Part D	Investigates switching costs and inertia in the Medicare Part D market, showing that switching costs are large and have important implications for the plans consumers are enrolled in.
Marton, Yelowitz, and Talbert (2015)	Medicaid Managed Care	Studies a policy where Medicaid enrollees in Kentucky were automatically enrolled in one of three managed-care plans and given 90 days to opt out. Some enrollees were defaulted into plans with their primary care physicians, and others were not (likely a poor option for them). 30 percent of all enrollees remain in matches without their primary care provider over a long time horizon, exhibiting evidence of substantial inertia in presence of default options.
Ericson and Starc (2013)	Massachusetts Exchange	Studies change in Massachusetts where exchange plans were required to standardize many financial dimensions of insurance products. Consumer valuation of certain attributes change, in manner that conforms more closely to rational valuation model.
Fang, Keane, and Silverman (2008)	Medigap	Studies choice in Medigap, with key result that consumers with limited cognitive ability may make poor choices, leading to adoption by the healthiest individuals (so-called advantageous selection).

In a large-employer insurance context, Handel and Kolstad (2015) document limited consumer information about plan options and the implications of that limited information for insurance purchase value. We link individual-level data on the insurance plan options available to them, the insurance plan actually chosen, and detailed medical claims. The study shows that consumers lack information on a range of important choice dimensions of the primary insurance options, including (i) financial characteristics (e.g., deductibles, coinsurance, out-of-pocket maximums), (ii) provider networks, and (iii) their own financial medical expenditure risks. Consumers in the bottom half of the population in terms of information about plan choices are willing to overpay $2,792 on average for more-generous insurance coverage, relative to identical consumers who are in the top quartile in terms of plan information. That is, low-information consumers are making systematically different choices that are costly even though when they actually enroll in the plan their experience would likely be similar to those who understand the choice environment better.

Bhargava, Loewenstein, and Sydnor (2015) present another clear example of the difficulties consumers have in making insurance decisions, also in a large-employer context. The authors study employee insurance choices at a firm that implemented a "build-your-own" insurance plan system, where employees could choose from 48 possible insurance plan designs. Notably, of these 48 options, many are dominated: regardless of the final level of realized medical expenditures, certain plans could never deliver greater financial value than other specific plan options. The authors document that many employees choose dominated plan options, and in the process overpay by an average of 42 percent of premiums for their medical care for the year (an overpayment on the order of magnitude of $1,000).

A range of studies document consumers leaving meaningful amounts of money on the table in the context of Medicare Part D, a prescription drug insurance program for the elderly that enrolled 37 million people in the United States in 2014. Medicare Part D has been a notorious example of a difficult product market for consumer choice; consumers across regions within the United States choose from a menu of thirty to forty plans, on average.

Abaluck and Gruber (2011) and Abaluck and Gruber (2014) document choice inconsistencies among the elderly, where an inconsistency represents money left on the table in the choice process. One nice feature of Medicare Part D is that, because it pertains only to prescription drugs for the elderly, it is easier to predict drug utilization/risk for the upcoming year for any given consumer than in a general health market. The authors find that, on average, consumers spend $300 to $400 more than what they would have spent in their cost-minimizing option, and that this gap is not diminished after accounting for heterogeneous consumer risks and consumer risk aversion. In their 2011 paper Abaluck and Gruber conclude that consumers lose 27 percent of the total cost of their medical care on average from these choice inconsistencies; the 2014 paper supports their earlier results. One key finding in both papers is that consumers overweight plan premiums, which are more salient, relative to underlying plan financial characteristics such as deductibles and copayment rates. Taking these findings one step farther, Kling et al. (2012) conduct an information provision campaign to seniors choosing Medicare Part D plans. They find that information provision does encourage seniors to switch to and select more-valuable plans for themselves, but that the number of consumers who remain in plans with much lower value than possible is still quite high. Importantly, the information provision in this study does not capture key components of insurance choice such as network and risk, one potential driver for the large remaining consumer group making suboptimal decisions.

Taken together, this literature points to clear choice errors that are both prevalent and costly even in environments where consumers make active choices. Providing personalized recommendations and decision support to consumers improves their choices. However, even effective personalized recommendation tools may not be enough to encourage active choice over time in the market—a necessary condition to realize the benefits of competition for consumers—if inertia is important and the market environment evolves over time, as is expected in the ACA exchanges. Instead, smart default policies may have the potential to be much more powerful for inactive consumers already in the market, who may not reevaluate their plan options each year.

Indeed, there is a large literature demonstrating that inertia plays an important role in reducing consumer choice effectiveness in health insurance markets. Handel (2013) finds that employees are willing to leave an average of $2,032 on the table in an environment where the plans from which consumers can choose changes quickly in the market from one year to the next. The study also documents a range of cases where consumers enroll in dominated insurance plan options (where they lose approximately $1,000 relative to another option in the best case scenario) and that new employees make substantially better choices than employees from prior years as the market evolves over time. In the Medicare Part D setting, several studies (Abaluck and Gruber 2014; Ericson 2014; Ho, Hogan, and Scott Morton 2015; Polyakova 2014) all document inertia and/or switching costs. Taken in sum, these papers illustrate that consumers lose a substantial amount of money from inertia above and beyond the money they leave on the table from active decisions, discussed earlier.

BOX 1.

Success of Smart Defaults in 401(K)

The movement toward default-based policies for retirement investment decisions (e.g., 401(k)) is an encouraging bellwether for bringing smart defaults to health insurance. Similar to insurance choice, prior empirical evidence from 401(k) elections and investments clearly pointed to large and meaningful consumer choices errors: people underinvest in general and also make suboptimal decisions about types of investments to make. Defaulting people into retirement savings levels, for example, at the full match rate of an employer, has proven to be a very effective way to enhance saving (see, e.g., Madrian and Shea 2001). Despite this, a major barrier to implementing a default policy was the difficulty in identifying individual preferences for risk and investment types: How can you default people into a savings plan without knowing their savings goals or how much risk they would like in their portfolio?

The advent of retirement age–targeted mixes of stocks and bonds, however, made feasible a default policy that was personal to that individual (based on age and retirement goals). Thus, in the domain of 401(k) choices, demographic information on age, income, and expected retirement date, coupled with a financial model of life-cycle consumption, allowed for smart default policies that have led to substantial improvements in consumer savings and lifetime welfare.

In a different setting—Medicaid in Kentucky—Marton, Yelowitz, and Talbert (2015) study a recent change whereby consumers were automatically enrolled in one of three managed care plans and given 90 days to opt out of those plans. Some enrollees were defaulted into plans with their primary care physicians, and other were not, indicating that that default was likely quite a poor option for them. The authors find that 30 percent of all enrollees remain in matches without their primary care provider over a long time horizon, exhibiting evidence of substantial inertia in the presence of default options. This suggests that default options, if well chosen, have the opportunity to substantially impact consumer enrollment and the value that consumers derive from insurance exchanges.

Though the literature has not been able to assess the impact that better consumer decisions would have on changing insurance product offerings in the market, the economic theory suggests that such effective consumer decision making is crucial for ensuring that the best possible products are offered in the market. Moreover, in establishing the goals for any policy or set of policies to facilitate consumer choice of health insurance products, there is an important distinction between the status quo of insurance options available on existing exchanges and new plan offerings and prices that might become available as insurers dynamically respond to consumer behavior and the entry of new exchanges. Smart policies can have an impact and generate social value in both cases. These are lofty goals given a long history of a lack of transparency, consumers' inability to make optimal decisions and, once they choose a plan, facing a series of "gotchas" in the form of unexpected costs if they need care. Insurers, on the other hand, have responded mainly by trying to lower cost and quality and avoid sick consumers. This combination has generated the kind of zero-sum competition that has characterized the U.S. health insurance market, and, some argue, U.S. health care as a whole (see e.g., Porter and Teisberg 2006). We are, however, optimistic that the United States is at a turning point due to the regulatory backbone created by the ACA—in particular the individual mandate and prohibition on pricing based on preexisting conditions—as well as the introduction of exchanges. Nevertheless, without smart policies to facilitate consumer choice, it will be difficult to see the welfare gains that innovation and competition have generated in other settings.

Chapter 3. The Proposal: Personalized Decision Support and Smart Defaults

Before expanding on the proposal in depth, we note that there are multiple goals for enhanced decision support that reflect the existing insurance options available as well as the broader set of plans that could be offered. The first goal of personalized decision support should be to enhance consumer welfare given the set of available insurance options on exchanges as they stand today. At a simple level, this requires moving consumers toward choices that best reflect their underlying preferences over health-care access, insurance product quality, and financial risk protection. Second, personalization and targeted recommendations will enhance competition among insurance plan offerings in order to lower prices and improve quality of the existing product offerings.

The two key features of our proposal require the CMS and state health exchange operators (i.e., the regulator) to:

1. Adopt and promote a narrow and more-targeted consumer search tool based on algorithms that assess consumers' projected needs and how they might experience each plan, and

2. Create an opt-out system of health insurance plan selection, where the regulator switches a consumer from a poorly matched to a well-matched plan during the open enrollment period, but only if the regulator is highly confident that the consumer would be made better off and if the consumer can easily switch back to the previous plan.

The core of our proposal is an extension to the requirement in the ACA that some form of consumer search tool must be provided by any ACA exchange.[1]

We propose CMS and the state exchanges use the authority in the ACA to develop more-precise and more-surgical decision support tools that take into account individual-specific characteristics, potential future health-care costs, and the underlying value of insurance resulting from expected financial outcomes, risk protection, and available in-network medical providers and services.

Given the paucity of such tools today, both in public exchanges and in longer-running private exchanges, there is a role for regulatory interventions to more carefully define the underlying elements of decision support. Specifically, decision support should (i) allow a specific individual to understand how much she can expect to spend in total for each plan, (ii) understand plan generosity that protects her from risk, and (iii) understand in a succinct and comparable way the quality of the network of physicians and hospitals in each plan.

Before we turn to the specific details, we note that in order to accomplish any goal of enhancing consumer decision making, creating smart defaults, or lowering the public budget cost of subsidies for health insurance, the necessary data infrastructure must exist to collect information about plans' benefit design and coverage of health-care networks, consumers' health needs, their preferences for providers, and so forth. (We refer the reader to box 2 for a discussion of the requisite data infrastructure components under different scenarios.) To support the necessary data infrastructure, we believe there is an important role for CMS and the state exchanges because comprehensive data collection is a public good—the social value of contribution is greater than the private value to each insurer who might contribute data. For example, there is evidence that insurers have strong reasons to obfuscate particular plan details, such as the cost of covering different types of illness or drugs, and the doctors or the hospitals that are in and out of network. To address the possibility of this kind of obfuscation, CMS and the state exchanges should strive to promote a robust and centralized data collection policy, and then integrate those data into their preferred method for improving consumer choices in the market. There are many ways, however, to assemble the data using both public sector and private sector resources. Therefore, we do not propose a specific type of data infrastructure but rather discuss the kinds of data that can support our proposal. Importantly, this discussion highlights that new data collection efforts are not prerequisites to developing either decision support or smart defaults, given the data and resources available today.

Next we describe several current distinct examples of exchange data infrastructures. Given what is currently seen in practice, and what seems reasonably possible in some environments, we discuss our policy proposals in the context of the following dimensions of data scale and depth:

- **Standardized descriptions of benefit design and coverage.** The first, and potentially simplest, of our proposed data collection strategies is that all participating insurers provide detailed information on the plans they offer using a standardized, machine readable file format. Today

BOX 2.

Enabling Next Generation Exchanges with Data Infrastructure

In this paper, we focus on choice policies in the context of what data environments are possible. In some cases, an exchange may not have the legal authority, stakeholder buy-in, or technological infrastructure to implement a detailed and comprehensive data collection and dissemination program. In some cases, such data collection is possible but not yet implemented, and in others such policies and data are already in place. We do not provide a general discussion of the different legal, political, and technological obstacles to a robust centralized exchange data collection platform, though we do discuss some related issues in the questions and concerns section at the end of the paper. For the policies discussed in this proposal, the crucial facts to keep in mind are that right now we see many different kinds of exchange data collection structures in practice, and that the effectiveness of the policies that we discuss depends on the scale and depth of those data.

most insurance companies provide a SERFF (System for Electronic Rate and Form Filing) file format description of their benefits. This is available for all insurers participating in HealthCare.gov and, in many cases, state exchanges. Throughout this proposal, we assume that such data are available and usable by the regulator, and potentially by third parties, as a backbone for plan recommendations and smart defaults.

- **Up-to-date information on hospital network inclusion and benefits.** The associated hospital and physician network an insurer develops is a key element that differentiates plans. In fact, network formation is one of the key dimensions under the ACA where insurers can create value relative to other insurers. Despite this, it remains a major challenge to access up-to-date information on coverage, even in more-mature private insurance markets such as Medicare Advantage. As innovation by insurers increasingly moves toward narrow networks, any ability of enrollees to make an informed choice or a regulator to provide a smart default will require understanding of (i) network breadth and (ii) an easily searchable and up-to-date database of plan providers. To date, insurers have been reticent to provide detail in a standardized format and, in most cases, require potential enrollees to access an insurer-provided lookup tool in order to assess coverage. Such fragmentation with little ability to assess accuracy is not and will not be sufficient to support next-generation exchanges, such as those we propose. Therefore, there is room for a regulatory approach to make these data available, given the public good nature of the problem. Throughout this proposal, we discuss a range of data environments, including those where such rich provider network level data are available and those where they are not.

- **Individual-Specific Health Information.** The policies we discuss will have different levels of effectiveness depending on the level of centralized, individual-specific health information that can be accessed by the regulator and/or third-party recommendation engines. We discuss our choice policies as a function of the different broad types of data that are seen in practice or may be reasonable to implement, including these:

  - **Basic Individual Demographic Information.** The data structure with the least detail we consider is one where basic demographics, such as age, gender, and income (e.g., from subsidy calculator), are known, but little else is known. Recommendations and smart default policies can still be quite useful in these environments, especially when used in conjunction with large nationally representative claims databases such as the Medical Expenditure Panel Survey (MEPS). That said, limiting the extent of individual-specific information at the time of purchase makes policies relatively less effective.

  - **User-Provided Health Information.** Many current environments allow users to input some health information, including past expenses, indicators of certain medical conditions, or general preferences related to provider networks. This information can provide important signals of appropriate plan choices.

  - **Limited Administrative Health Information.** In certain cases, exchanges or employers are able to centralize limited administrative health information without collecting detailed individual-level claims data. These data provide individual-specific indicators of past health conditions or spending, but not highly detailed data of past health incidents.

  - **All-Payer Claims Database.** An all-payer claims database (APCD) incorporates medical claims at the individual level from all insurers participating in a given exchange. We take this to be the gold standard for data given the policies we discuss. These data can be used at the individual level to either recommend plans or implement smart defaults in a highly targeted way for each individual at the time of plan choice. Integrating such data in a centralized way, such that it can be used for the policies we discuss, is certainly possible; such use also faces legal and political difficulties in some settings, however.

Many current exchanges have fairly limited individual-specific data: it is crucial to note that the policies we discuss can still be implemented by effectively harnessing alternative data sources and relying on predictive and matching models. This emphasis is particularly relevant given the upcoming Supreme Court decision in *Gobeille v. Liberty Mutual Insurance Co.* (2015) which may limit the ability of APCD operators to subpoena data from private insurers. Were that ruling to go the way of the insurance carriers, it would still be feasible to implement all of the proposed policies here.

Though not the primary focus of this article, we believe that a comprehensive, national regulatory standard that makes clear what data must be reported and provides a uniform format to report those data should be developed for state-based exchanges and other government-regulated insurance markets. This standard should strive to provide as much data depth as legally and politically feasible in order to facilitate basic research, as well as the implementation of choice policies by regulators and third-party companies, whose work will be critical to realizing the value of the underlying data.[2]

PERSONALIZED INFORMATION PROVISION AND RECOMMENDATIONS

We now describe what we view as the key elements of personalized information provision in turn, including

- Individualized plan cost calculator for hospital and physician services,
- Individualized plan cost calculator for prescription drug coverage,
- Critical aggregate information about the breadth and quality of the plan hospital and physician provider network,
- Specific information about the overlap between the plan provider network and an individual's current providers, and
- An assessment of plan risk protection in the context of individual-specific risks and risk preferences.

First, any personalized decision support should allow an individual to understand how much she can actually expect to spend in each plan offered to her. This information should be provided as a total, plan- and individual-specific, expected out-of-pocket cost number.[3] Cost calculators should incorporate both the cost of potential hospital and physician services an individual is likely to consume as well as her cost to take medications under each plan. While these are all covered health benefits, the data infrastructure often distinguishes these two elements.

There are many different approaches to computing costs and integrating personal preferences. The kind of decision support we propose relies on algorithms to assess consumers and understand how they might experience each plan. These predictive models mirror the kinds of personalized decision support and product recommendation that have been developed in online marketplaces beyond health care (e.g., Amazon, Netflix). Specifically, an individual, predictive cost calculator will take information an individual can supply (e.g., age, gender, zip code, drugs taken). Using these data, the algorithm will then rely on a large, representative set of data to produce a prediction for that individual of how much she can expect to spend in each plan. This prediction is informed by, potentially, millions of other individuals' actual medical experiences and the detailed data on the insurance benefits. In addition to predicting the average experience, it also allows for an assessment of "good" and "bad" scenarios, again based on individuals' actual experience. That is, a user who enters only a small amount of information will get as accurate a prediction as possible of how much she specifically will spend in each plan on average, were she (i) to stay healthy and were she (ii) to require substantial medical care.

The goal of any approach is to yield the kind of information that is critical to informed consumer choice: a clear understanding of expected cost in each plan offering. Critically, these proposed cost calculators are (i) forward looking and (ii) personalized. That is, they take into account future health-care states for a specific individual. This stands in contrast to some existing cost calculator tools that either use average enrollees in the whole population (e.g., the mean of data from the MEPS) or past years' claims run through future year benefits (e.g., asking about planned events such as surgeries in the next year). These existing approaches are not without merit, but both are insufficient to yield the kind of individual choice that encourages insurers to compete for their business. Other decision support tools that rely on extensive questionnaires, notably asking about planned health spending, are unlikely to recover valuable information (recall that individuals have difficulty accurately understanding health risks and cost), and may also exacerbate adverse selection, undermining the value of competition in the marketplace.

In addition to simply understanding the average experience an individual can expect in each plan, true decision support in insurance markets must address the fundamental reason people purchase insurance: risk protection. As we discussed, risk aversion is manifested in insurance purchases as an increase in willingness to pay fixed amounts in premiums to enhance coverage in case of illness or injury. Decision support should allow individuals to make that assessment in choosing an insurance plan by allowing them to understand how well a plan covers them under different scenarios or health outcomes. This should include assessments of both in-network and out-of-network scenarios, alongside information about network breadth and quality.

This type of personal decision support could take on different forms. As in the cost calculator case, tools can be developed that assess different scenarios for individuals as well as their preferences on a predictive basis. Given sufficient data, individuals could then understand the risk protective value of a benefit in totality without having to do a lot of computation themselves. For example, suppose a Medicare enrollee is choosing between two Medicare Part D benefit options to cover her for drug spending. Suppose that for the current medications she is taking she has precisely the same expected out-of-pocket cost—the premium plus the cost sharing for those drugs. Suppose further that one of the plans has a much more restrictive formulary that does not cover many frequently prescribed drugs. A risk-averse consumer—and appropriate decision support for that consumer—would prefer the more generous formulary based not on the state of the world today, but rather on the fact that the potential downside is larger (high variance) in the plan with less coverage for the same price today. While this kind of thinking adheres to our understanding of why people buy insurance, this kind of decision support has rarely been implemented in practice.

Alternatively, some proposed decision support tools allow individuals to understand different cases of what spending in each plan might look like. For example, a best-case, medium-case, and worst-case scenario can be provided for each plan and an individual can trade that off against the premium for each. While this has appeal, scenario-based decision support tools can potentially exacerbate the very choice errors they seek to alleviate. For example, we already know that people have difficulties in understanding probabilities, particularly when assessing low-probability events, and place excessive weight on premiums relative to future out-of-pocket expenses (e.g., Abaluck and Gruber 2011, 2014; Bhargava, Loewenstein, and Sydnor 2015; Handel and Kolstad 2015). Thus, telling people worst-case scenarios may well lead to a strong response, even in cases where such an outcome is highly unlikely. Given these drawbacks, we support the first approach: relying on personalized recommendation algorithms akin to those found in non-health-care marketplaces.

In addition to the tools described above, which focus primarily on the financial aspect of insurance products, we also propose a comprehensive tool that will allow individuals to assess the networks of hospitals and physicians available in the plans from which they are choosing. Evidence suggests this feature is an important element of choice in insurance products (e.g., Ho 2009). It is also an increasing source of differentiation and innovation for insurers tackling cost with so-called narrow network plans. For these kinds of plans to truly generate the gains hoped for—higher-value health care—consumers must be able to understand what they are gaining or giving up in moving from one plan to another. Plans that offer lower cost options but leave consumers paying out-of-pocket for care because of a "gotcha" in the network of physicians covered do not constitute innovation, in our view. For example, a network might include Hospital A, but some physicians at that hospital are actually out of network; if they end up treating a patient at the in-network hospital, the patient might have to pay the doctor out of pocket. To address this issue, exchanges should offer some form of tool that will allow individuals (or families) to understand coverage across plans.

There are two primary approaches to network decision tools, though they are not mutually exclusive. The first is simply providing the ability for individuals to sort/screen out plans based on whether specific doctors, hospitals, or both are included. The second approach seeks to incorporate a broader notion of overall network value/coverage into decision support. The first approach is simpler to implement because it merely requires a clear data set on networks for each plan offering.

Using the first approach alone, while simpler, can leave individuals without the ability to clearly trade off cost and network generosity. For example, suppose a consumer has visited a specialist once for a minor treatment. She may have little value in seeing that doctor again but has him on a list of visited physicians (particularly in cases in which decision support draws from a provider list generated from previous health-care claims). Simply eliminating or sorting out plan options not including that doctor might leave the consumer seeing only a handful of options without the ability to understand how much lower premiums would be were she to move to plans without that doctor in the network. Thus, network evaluation tools that allow individuals to understand the cost (and risk protective benefits) for all plans, including those without coverage for some or all of their hospital and physician preferences, is an important feature to allow for informed consumer choice.

Tools that extend this approach to account for the value of access to hospitals or doctors based on the expected utilization and preferences for an individual can provide value by simplifying demands placed on consumers. They can eliminate the need to configure and reconfigure different network combinations to trade off cost against network but, as above, require sufficient data infrastructure and analytic capability.

Regardless of the approach, incorporating demonstrations of individualized risk protective benefits and network or service quality into decision support is fundamental to a well-functioning marketplace. Individuals will be better aligned to plans given the existing set of options. In addition, incorporating risk into choices is critical to generating a sustainable marketplace because it pools people who are willing to pay for additional risk protection or network/service quality with those who are relatively sick, and therefore value generous coverage due to expected cost. In the absence of such pooling—for example, in the case in which people merely choose plans based on planned surgeries or on past years' costs, as is the case with

TABLE 2.

Plan Values in Different Choice Scenarios

	Value over Worst Plan*	Value over Chosen Plan*	Percent Sample Benefiting	Percent of Sample Losing	Average Benefit*	Average Loss*
Chosen Plan	25.79%	0.00%	0.00%	0.00%	0.00%	0.00%
Random Plan	20.14%	–5.65%	32.30%	51.55%	12.23%	–18.62%
Best Possible Plan	35.33%	9.54%	74.79%	0.00%	12.75%	0.00%
Age-Gender Best Plan	29.82%	4.03%	52.45%	25.63%	13.32%	–11.54%

* As percent over average annual premium paid.

most decision support today—adverse selection can undermine both pricing of plans (raising cost for more generous benefits) and, in the extreme, lead to elimination of plans completely or lack of entry by innovative, more-generous benefits.

EXAMPLE: APPLICATION OF PERSONALIZED RECOMMENDATIONS

In order to illustrate the important impact that personalized recommendations could have in health insurance markets, we set up a simple consumer choice simulation. Though intended to be illustrative only, we chose model parameters such that consumer and health plan characteristics are similar to those actually seen in practice. The technical details of the simulation are presented in appendix A.

In our example, we study several illustrative plans similar to those that could be found for single females between the ages of 19 and 44 who are on the Covered California insurance exchange. Our simulation assumes there are six different plan options available to consumers, characterized by

- **Network:** Two distinct insurers, each offering a unique provider network in each financial tier;
- **Financial tier:** Bronze (60%), Silver (70%), Gold (80%); and
- **Premiums:** Plan-specific premiums.

The details of each plan are provided in the technical appendix.

We simulate a population of 10,000 19- to 44-year-old females with the following characteristics that differ in the following ways:

- **Health risk.** We use nationally representative data to assess the likelihood of different expected health spending amounts for women in this age range. We also project risk around those expected expenditures for each population member.
- **Risk aversion.** We simulate consumer demand for risk protection using numbers similar to those estimated in the academic literature.
- **Choice frictions.** We model differences in decision-making quality by simulating consumer misperceptions about plan value, with variation across individuals similar to those found in the literature.
- **Network value.** We simulate heterogeneous valuations for each of the two provider networks offered.

Given the insurance options available, for each consumer we use these characteristics to compute the corresponding value for each plan option in the market.

Table 2 illustrates the amount that consumers could save via personalized recommendations as a function of different underlying decision support tools using different data elements. The top row studies the simulated choices consumers make, given their characteristics, if they chose on their own with no personalized decision support. Consumers in this example lose value equal to 9.5 percent of their mean annual premium when choosing on their own, relative to their best possible choice.

The second row studies consumer well-being when she is randomly allocated to any plan in the market, relative to the environment where she chose on her own. This very roughly mimics an environment with substantial consumer confusion, and is precisely the mechanism used to default low-income consumers into plans in Medicare Part D. Under random assignment, consumers are worse off by an average of 5.7 percent (of their mean annual premium) than when choosing on their own. Relative to choosing on their own, 32.3 percent of consumers are better off (with an average benefit of 12.2 percent of spending) under random choice, and 51.6 percent are worse off (with 18.6 percent average loss).

The best possible plan scenario referred to above mimics the case where (i) the regulator has ideal data, (ii) personalized plan recommendations are available, and (iii) consumers always act on those recommendations. In that case, about 75 percent of consumers are better off than if they chose on their own. If consumers only sometimes act on these recommendations, the relative value under recommendations with ideal data will be somewhere in between the outcomes under the first row (choice alone) and the third row (best possible outcome).

The fourth row examines a recommendation scenario where the data are not ideal, and the regulator observes only individual age and gender. Consumer welfare improves by 4.0 percent of annual premium paid, relative to choice with no recommendation, less than half of the way to the improvement that occurs under recommendations with ideal data and decision support. Under this less-precise recommendation, 52.5 percent of consumers are better off than under choice alone, but 25.6 percent are worse off if they follow the recommendation.

The example in table 2 illustrates the potential value and trade-offs present for targeted personal recommendations under different data environments. We reexamine the nuances of our smart default policy in the context of this simulation after describing our policy proposal.

SMART DEFAULTS AND EXPLICIT NUDGING

The second prong of our proposal recognizes that, as discussed above, inertia and passive choice architecture can have a large negative impact on the value consumers derive from insurance exchanges. Here we move beyond merely enhancing the ability of individuals to make smarter and more-personalized choice across insurance plans. Under our smart default policy, an individual will be defaulted into a plan that is predicted to best provide low-cost, high-quality care for that individual. Using the same tools available to allow for personalized search, exchange operators and regulators will automatically enroll individuals in the plan that is best predicted to fit their needs. All enrollees would still have the ability to opt out of the default and instead choose any of the available plans for them. This is the so-called libertarian paternalism approach espoused in the book *Nudge* (Thaler and Sunstein 2008).

Given the evidence on consumer inertia and its implications for plan choice, smart default policies could dramatically improve consumer satisfaction with insurance plans and reduce government budgets, simply by nudging consumers toward more-valuable choices when it is clear that those choices are in fact more valuable. The effectiveness of smart default policies relies crucially on the regulator having access to (i) consumer-specific information and (ii) a trustworthy underlying model of when choosing a poorly aligned plan is especially costly.

Smart Defaults in Health Insurance

We now describe our smart default policy in greater detail. Critically, we assume that the models necessary to support individual insurance choice and understand individual value in each plan—the tools we describe above—have been implemented. That is, smart defaults rely on individual decision support to determine the appropriate default (where the "smart" comes from). We further assume that the data necessary to determine how much consumers would value insurance plans are available, because such data do exist today (see box 2).[4]

The design of our smart default model will have three primary model components:

1. **Increase in expected plan value.** Consumers' expected financial benefit from the new default option, relative to their current plan, should be greater than some amount that depends on the confidence the regulator has in its assessment of insurance plans and consumer heterogeneity. Regulators will develop and use statistical models of health risk based on administrative individual-level health risk data to predict the probabilities of different levels of total medical spending in the next year. Regulators will combine this model of health risk with a model of insurance plan payments (for each plan in the market) to assess the expected financial benefit from the new default. We present an example of the approach, in the section "Application of Smart Defaults."

2. **Minimal extra risk exposure.** Consumers' maximum financial loss from the new default option, relative to their current plan, should be less than some amount. This threshold should depend on income, family status, and consumer-provided information on risk aversion, if observed. The regulator will develop the maximum financial loss statistic based on a careful model of insurance plan designs.

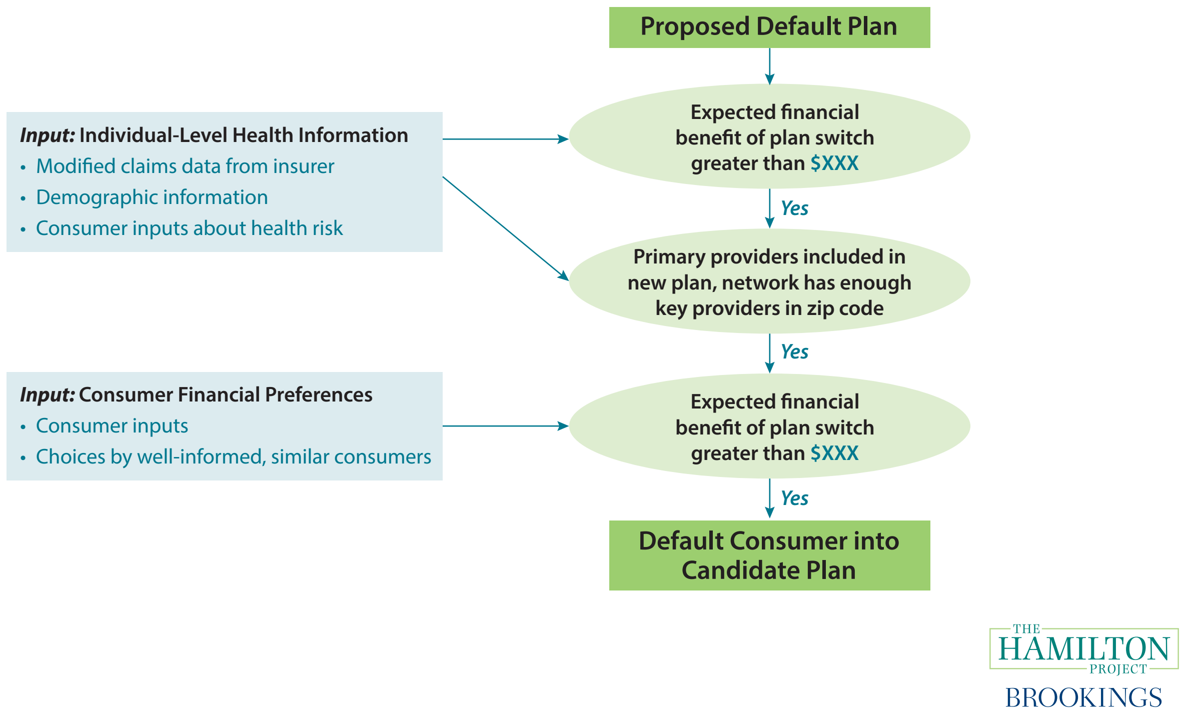
3. **Provider continuity.** Consumers' new default option should contain all medical providers from which the consumers have regularly received care over the last two years. Regular visits would be defined by a regulator and could be health-condition specific. If key regular providers are not in network for a candidate default option, consumers will not be defaulted into that option. In addition, the regulator will characterize network breadth of a given plan in general, and not default the consumer into a plan with substantially lower value for providers in network within a given radius of that consumer's zip code.

Figure 1 displays these conditions for a smart default and specifies the inputs necessary, and conditions required for the consumer to be defaulted into a different plan option.

Specific regulators can fine-tune their smart default policy to be more or less aggressive depending on how they weight the potential gains in value relative to the losses that might occur through misassignment when implementing smart defaults manifest in their respective environments. A more aggressive policy would reduce the expected value threshold, increase the maximum worst-case risk threshold, and reduce the threshold

FIGURE 1.

Smart Default Example



for how narrow the new default plan provider network is. The regulator could thus implement this policy in a manner that defaults only, for example, the 1 percent of the sample who are leaving substantial value on the table into a new plan, or, for example, 50 percent of consumers who seem to be leaving some value on the table.

If effectively implemented, these smart defaults not only ensure that consumers are not leaving substantial value on the table in their insurance choices, but also allow them to actively return to a previous plan or choose from the full menu of options. That is, for active consumers full choice agency is maintained but for passive consumers major errors are avoided and, in most cases, such consumers are aligned with an optimal or near-optimal plan. This directly links to (i) improved consumer welfare, (ii) reduced government subsidies to insurers, and (iii) potentially increased insurer competition, feeding back into lower premiums and higher product quality. Ho, Hogan, and Scott Morton (2015) illustrate this in the context of Medicare Part D: in their analysis, when consumer inertia is fully removed (e.g., by a fully effective smart default policy) insurer premiums are reduced substantially, leading to $550 million in government savings in their market over three years, and providing each consumer with an average $563 benefit. While that analysis does not investigate changes to product quality or regulatory capture—the ability of firms to influence the design of smart defaults—it does nicely illustrate the potential gains from more-fluid consumer choices in insurance exchanges.

In cases where the federal government is subsidizing enrollee cost-sharing or premiums, we argue that there is both an opportunity and a clear rationale to take decision support one step farther. In many cases, choice errors are not dramatically impacting those individuals enrolling in insurance because cost sharing is partially or fully covered by subsidies. Instead, much of the burden falls on federal government budgets. Just considering the Medicare Part D market alone, a simple version of this policy was predicted to generate savings of $5 billion a year in the low-income subsidy (LIS) market, where nearly the full burden of poor choice is borne by the federal government (Zhang et al. 2014). We discuss this in more detail in box 3.

EXAMPLE: APPLICATION OF SMART DEFAULTS

In order to clarify the form and inherent trade-offs of a potential smart default policy, we return to the simulated environment studied at the end of the section "Example: Application of Personalized Recommendations"; this simulation is described in detail in the technical appendix. See those sections for detailed information on the microfoundations underpinning this simulated market and the consumers in that market.

BOX 3.

Medicare Part D: A Case Study in Smart Defaults and Government Spending

Medicare Part D provides a unique case study that underscores the potential fiscal impact of a smart default–based policy. In fact, we would argue for Medicare Part D as a natural initial context in which to implement such a policy.

Because Medicare Part D covers only drugs, consumer choice tools (e.g., at Medicare.gov) provide a far greater degree of personalization and prediction than in other settings (e.g., at HealthCare.gov) without substantial modeling and investment. While there remain some shortcomings such as incorporation of consumers' risk exposure and risk aversion of consumers, a default based on current drugs taken would fit our definition of a smart default. Zhang et al. (2014) study the impact a reassignment policy would have in the Medicare Part D LIS population. In effect, such a policy assumes complete compliance with the default approach. While this is likely to overestimate the impact of a nudge, given the high estimated switching costs in health insurance, the fact that the target is based on the expected cost and the substantial impact of defaults in other settings, this is a reasonable assessment of the potential for a smart default policy for Medicare Part D.

Enrollees with sufficiently low income pay only a small share of the premium and out-of-pocket cost for drugs when enrolling in Medicare Part D. The LIS component of the program is large: of the $60 billion spent on Medicare Part D, approximately 75 percent was for LIS-eligible enrollees (CBO 2014). The high cost stems in part from the number of people who are eligible for the subsidy. However, a major contributor is the fact that LIS enrollee out-of-pocket costs are almost entirely paid for by the federal government for nearly any Part D plan they choose. (There are exceptions for very-high-cost plans but these are rarely selected.) Furthermore, in assigning individuals who qualify for LIS to plans, the regulatory approach taken is random assignment to any plan whose premium is sufficiently low (i.e., meets the benchmark CMS sets annually). The majority of plans meet this benchmark in most CMS regions (states or groups of states that define a market for Part D). Therefore, the policy approach today is to randomly allocate individuals across Part D plans with widely varying levels of coverage for different drugs, both with respect to out-of-pocket cost exposure, and with respect to formulary and review requirement for drugs. This has some impact on the enrollees themselves, through higher cost and utilization review, but the majority of the impact falls on the federal government, which pays the out-of-pocket cost component. In other words, from a financial perspective, enrollees are largely indifferent and have little incentive to switch based on the drugs they take, but there is substantial difference in cost between plans for the Medicare program.

Zhang et al. (2014) estimate that, using data from the 2009 enrollment year, moving from a random assignment of individuals to plans to assigning them to the plan with the lowest expected cost based on the drugs taken by that individual in 2008 would generate savings of $5 billion annually for the program. The average savings per enrollee would be $738 per year. These savings would accrue to both the individual enrollees and the federal government, though due to the generous subsidy the majority of the value ($710 per enrollee) would be accrued to the government. In addition to the financial impact, if individuals were reassigned, Zhang et al. (2014) estimate they would see a 45 percent reduction in the share of their drugs that require utilization review. That is, people who are already taking specific drugs are being assigned (randomly) to plans that limit coverage—or at least create barriers in the form of review—for those very drugs.

This case underscores the potential value to a smart default policy for both the enrollees and, particularly in this case, government fiscal burden. The current policy that is predicated at least in part on not wanting to interfere with consumer autonomy, or to pick "winners" among health plans, has led to individuals being randomly allocated to plans that differ substantially in how well they match their actual needs. Given available tools—in this case a simple drug cost calculator already provided through Medicare.gov—an individual's match to a plan can be computed with a great degree of accuracy prior to assignment. While the estimated impact of total reassignment may be higher than the actual impact of a smart default with opt-out by consumers, the results underscore the potential benefits the policy might have for enrollees in terms of reduced costs, hassle, and review requirements. Furthermore, if a policy were to merely default the individual into the plan predicted to have the lowest out-of-pocket cost, individuals' abilities to switch to a plan that they preferred for other reasons would be maintained. Beyond the benefits that might accrue to such a policy given the existing set of plans and prices, a smart default policy would have the added effect of enhancing competition in benefit design and potentially moving the marketplace toward offering plans that provide greater overall value rather than targeting consumers who overemphasize the premium. Because insurers have to offer the same benefit structures to LIS and non-LIS enrollees, the reliance on smart defaults would have spillover effects on the broader population. With a smart default policy, insurers would have strong incentives to offer plans that both reduce premiums and provide coverage that is more generous overall. Rather than relying on consumers' focus on premium alone by lowering premiums and raising out-of-pocket cost sharing, plans would win business by providing more-comprehensive coverage for a lower cost.

TABLE 3.

Plan Values under Smart Default Policies

	Value over Worst Plan*	Value over Chosen Plan*	Percent Sample Benefitting	Percent of Sample Losing	Average Benefit*	Average Loss*
Chosen Plan	25.79%	0.00%	0.00%	0.00%	0.00%	0.00%
Randomized Plan	20.14%	-5.65%	32.30%	51.55%	12.23%	-18.62%
Best Possible Plan	35.33%	9.54%	74.79%	0.00%	12.75%	0.00%
Age-Gender Best Plan	29.82%	4.03%	52.45%	25.63%	13.32%	-11.54%
Predicted Best Plan: $0 Reservation	31.49%	5.69%	54.68%	22.51%	13.30%	-7.01%
Predicted Best Plan: $200 Reservation	31.00%	5.21%	38.76%	11.75%	15.71%	-7.52%
Predicted Best Plan: $400 Reservation	29.91%	4.12%	24.72%	5.57%	18.65%	-8.88%
Predicted Best Plan: $800 Reservation	27.74%	1.95%	7.86%	1.99%	27.15%	-9.37%

* As % of Mean Annual Premium

Table 3 repeats the results from the personalized recommendation scenarios described earlier, and adds results for a set of smart default policies characterized as follows:

- The regulator has access to reasonably detailed claims data that it uses to form a model of consumers' values for different plans. These data are not ideal, but provide a strong signal of plan value.
- The regulator defaults a consumer into a plan if the model predicts the consumer will gain at least some specified amount from switching. We study values of $0, $200, $400, and $800.
- We assume the market is a new market, such that consumers have not already chosen a plan with specific providers. A policy with existing consumer choices would respect consumer provider network preferences as well.
- The consumer remains in a new plan if she is defaulted into one. In reality, she could switch back or to another option if she wishes.

Row 1 represents consumers' chosen plans under the model described earlier, and row 2 describes consumers' relative value if they are randomly allocated to plans. Row 3, representing the true best possible choice, can be viewed as the outcome under ideal data with personalized recommendations that are always acted on, or a smart default policy implemented with ideal data where no consumer switches from the default. Row 4 describes either fully acted on personalized recommendations, or smart defaults, when the data available to support choice policies are limited to age and gender. Note that when the data used to set the smart default are more limited, the majority of consumers gain, but some actually lose. This occurs because even knowing someone's age and gender leaves differences in health-care use that will mean some people are made worse off; without more-detailed information to predict use, some individuals end up in plans that are worse than their previously chosen plan. The potential for value for an individual in a plan not captured by the algorithm underscores the importance of allowing individuals to opt out of default plans.

Rows 5 to 8 illustrate the impacts of the different smart default policies using ideal data, corresponding to the different thresholds for switching consumers. As the threshold for switching consumers rises, from $0 (row 5) to $800 (row 8), the smart policy becomes more conservative: fewer consumers gain from the policy, but at the same time fewer consumers experience negative outcomes where they are defaulted into a plan that is worse than the plan they would have chosen on their own.[5]

For example, for default thresholds of $0, $400, and $800, respectively, consumers are on average 5.7 percent, 4.1 percent, and 2.0 percent better off than they would have been with no policy and just their own free choice. For these three scenarios, 54.7 percent, 24.7 percent, and 7.9 percent of consumers are better off, respectively, than if no smart default policy were in place. However, the statistic on percentage of consumers that are worse off under the smart default policies illustrates the potential negative consequences of smart default policies. In fact, 22.5 percent of consumers are worse off under the smart default policy with a $0 threshold, while only 5.6 percent and 2.0 percent are worse off under smart default policies with $400 and $800 thresholds, respectively.

Thus, while consumers are better off on average in our simulation under more-aggressive smart defaults, there are also more “losers” under that policy. In our simulation, this policy is also comparable to a smart default policy based on age and gender alone, where 52.5 percent of consumers are better off but 25.6 percent are worse off.

Finally, we note that as the threshold for the smart default policy rises, the average benefit for consumers who gain from the policy rises substantially (from 13.3 percent to 27.2 percent), while the average loss remains relatively constant. This suggests that as the threshold is raised, the consumers most in need of a plan switch are still benefiting from the smart default policy, while fewer consumers are losing out.

It is worth noting here that the assumption that consumers actually follow plan recommendations in our analysis of personalized recommendation is an important one when comparing those policies to smart default policies. Research suggests that many consumers will not follow plan recommendations (though these studies generally consider decision support without the personalization and prediction we propose), but that smart defaults will be very effective in switching consumers—in other words, many will remain in the default. Thus, while our simulation illustrates the potential benefits of each policy, the results/trade-offs exposited should be viewed in light of those assumptions.

Chapter 4. Discussion

There is little doubt that, given reasonably detailed available data and the current market structure, a smart default policy will be the most effective of the policies we study in encouraging consumers to enroll in high-value insurance options. This means that, holding the available set of plans as fixed, a carefully crafted smart default policy should always deliver more value than less-effective policies, such as information provision on its own. Since information provision can always be implemented alongside smart defaults, and if smart defaults are effective in getting some inertial, or even active, consumers to switch coverage, as evidence suggests, then implementing a smart default policy will improve consumers' insurance choices.

That said, policymakers in any given market should also assess whether smart default will be too effective in getting consumers to switch insurance plans. If smart defaults are very effective in getting consumers to switch, it could be because the regulator is doing a good job of choosing those smart defaults, or because inertia implies that consumers will rarely change away from their default option, even if it is a worse option for them (this was highlighted in our example at the end of the last section). Moreover, if the regulator's smart default option is not sufficiently nuanced, it may end up steering many consumers toward one or two insurance options and have a substantial impact on competition in the market. This clustering could either reduce competition in the market by favoring one insurer at the expense of others, or lead to regulatory capture where insurers and lobbyists get the regulator to steer consumers toward their plans. Additionally, insurers could try to game the smart default system to attract consumers by improving plans on certain dimensions and reducing coverage on dimensions not sufficiently valued by the smart default algorithm. This kind of algorithm-based shift in the market is well-documented in many settings, such as in the shift in website design to enhance rankings in Google search results (Lazer et al. 2014). Thus, while smart defaults have the potential to increase competition by effectively creating more price- and value-sensitive consumers, the defaults also have the potential to harm competition by heavily favoring certain options and moving large market share toward those options. Table 4 summarizes these potential pitfalls of smart default policies, alongside their potential advantages as discussed throughout this proposal.

Figure 2 explores the range of policies we propose in terms of (i) how effective the policies are in improving choices, given market structure, and (ii) the degree of consumer agency that

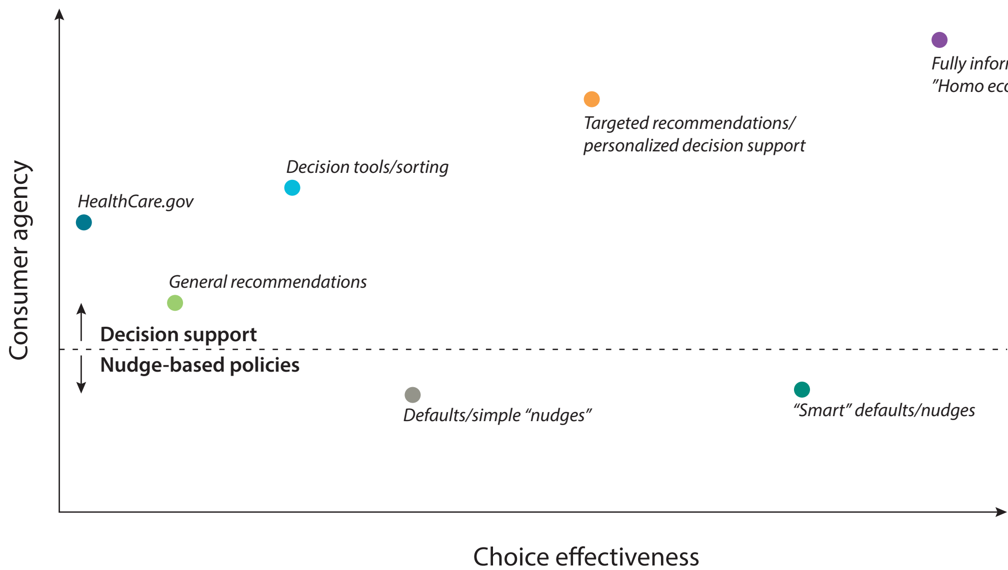
TABLE 4.

Potential Pros and Cons of Smart Default Policies

Gains in Welfare	Potential Challenges
The extra value created for consumers by more-aggressive policies (e.g., smart defaults) given the current market structure	Value lost for inertial consumers because the smart default policy moves them to a policy that is worse for them
The extra value created for the government by more-aggressive policies from lower subsidies and budget commitment	Value lost for consumers when competition is reduced because the smart default system overly favors certain plan options (whether inadvertently or due to regulatory capture)
The extra value created for consumers by more-aggressive policies as market structure changes, prices are lowered, and plan qualities improve	Value lost for consumers when insurers game the smart default algorithm and deliver low quality on dimensions that algorithm does not value

FIGURE 2.

Choice Policies: Consumer Agency and Choice Effectiveness



is reflected in insurance enrollment. Decision support policies that don't explicitly steer consumers into certain plans allow a greater degree of overall consumer agency in insurance enrollments but may be less effective than policies that do explicitly steer consumers into certain valuable options.

While quantifying these trade-offs is beyond the scope of current economic research on competition in health plan markets, the potential negative consequences of more-aggressive choices policies should be mitigated as the data used to support those policies become stronger, as the ability of insurers to capture the regulator becomes lower, and as the heterogeneity in plan recommendations becomes more extensive. If, for example, the smart default algorithms switches 15 percent of consumers in the market, and switches them to a range of different insurance options, it is fairly clear that regulatory capture and algorithms that favor specific insurers are not a major issue. (The converse would suggest that these are important issues). To this end, regulators could implement a policy that limits the percentage of consumers in the market that can be defaulted into a given insurance option (with a mechanism for determining the consumers with the most to gain from that default option). This limit would be effective in situations where regulatory capture or models that favor specific insurance plans are issues.

Chapter 5. Questions and Concerns

Given the challenges exchanges have already faced (e.g., HealthCare.gov) why intervene?

One policy option is, of course, the path of doing nothing. While this would leave the kind of choice errors that are well documented, there is some evidence that over time individuals are able to learn and so improve their choices (e.g., Ketcham, Lucarelli, and Powers 2015). Despite this optimistic view, Medicare has provided a variety of plan options for prescription drug plans since 2006 and in Medicare Advantage for many decades. Given the continued choice errors in those markets, the evidence does not suggest the market alone is likely to yield the kinds of smart choices required to achieve policy goals (Abaluck and Gruber 2011, 2014). It is also important to be clear that not intervening is still a conscious choice; selecting not to use decision support or defaults defines the choice environment and yields an associated set of market outcomes. That is, we believe regulators and exchange operators should make the same active choices we espouse for insurance enrollees they are helping.

Most exchanges today report that they offer "decision support." How is this proposal different from that support?

Exchange operators today are working hard to enhance consumer experiences and many report providing decision support. Therefore, we want to make clear what we consider to be outside the scope of personalization and/or decision support, despite frequent efforts to brand these tools as such.

First, merely providing a detailed matrix on the plan options available to consumers and allowing them to sort by some of these features does not achieve the goals we have outlined. Most exchanges today have some form of this tool. For example, HealthCare.gov allows users to understand the premiums and coverage detail of each plan option. Similarly, Medicare.gov allows a consumer to see all of the available prescription drug plans in her zip code and sort based on premium, total cost for her current drugs, or other features of the plan. In the absence of the ability to synthesize such information and use it to make forward-looking plan choices, providing additional information may not enhance consumer choices. In fact, the kinds of sorting engines and information provision available today may be important contributors to choice errors.

Beyond provision of plan information that is uniform across consumers, some exchanges/consumer choice tools look to provide general recommendations and calculators that, effectively, allow consumers to input a set of criteria or characteristics and use the elements of insurance options to make a recommendation or present a scenario. Perhaps the best-known, and most-studied, version of such a tool is the cost calculator for Medicare Part D plans on Medicare.gov. That calculator allows an individual to input the drugs she is taking and understand how much each plan will cost her in terms of monthly premium and total out-of-pocket cost. Related tools of this type include subsidy calculators on ACA exchanges that allow individuals to input their income and receive information on the actual premiums they will face, depending on their subsidy level. Some exchanges, largely those that are private, also allow individuals to report conditions they have (e.g., pregnancy, etc.) or procedures they are planning (e.g., surgeries, etc.) to estimate the accompanying out-of-pocket costs.

There are two main concerns with regard to these kinds of simple calculators. First, the evidence does not provide strong support that access to simple calculators alone is sufficient to enhance consumer choice. The experience in the Medicare Part D market provides a cautionary tale as the evidence suggests substantial continued choice errors in that market (e.g., Abaluck and Gruber 2011; Kling et al 2012). Second, and more fundamental from a policy or exchange operator perspective, enhancing sorting on existing conditions or drugs taken can dramatically exacerbate adverse selection because sick people are steered to more-generous coverage and healthier people are steered to the opposite. Therefore, while intuitively appealing, decision support that relies on asking about planned events may be worse than not having decision support at all, depending on the setting.

Your proposal discusses how detailed and centralized data are quite helpful for implementing more-aggressive choice policies, though these data are not essential for weaker policies. What are the barriers to such robust and centralized data collection and why don't all exchanges automatically implement the most detailed data environment possible?

Fully answering this question is beyond the scope of this paper. There are many legal and political obstacles, especially in certain states, that stand in the way of implementing something like an integrated APCD, including the following:

- Insurers may be unwilling to share their data, and may not be compelled to do so. This may be especially true if their claims data contain proprietary information. We argue that this kind of information can be removed without really hurting the detail of the data that are useful for choice policy. This is a very prescient issue, at the heart of the upcoming Supreme Court Decision *Gobeille v. Liberty Mutual Insurance Co.* (2015) that may limit the ability of APCD operators to subpoena data from private insurers.

- Though not a long-run barrier, in the short run many insurers and state governments may lack the technological expertise or data infrastructure themselves to contribute to or to build a centralized system. While this can be rectified over time, it remains a short-run barrier. Leveraging outside vendors who are able to develop these tools and harness existing data is a plausible and, likely, efficient solution, particularly in the short term.

- Medical privacy law (e.g., Health Insurance Portability and Accountability Act of 1996 [HIPAA]) could restrict the way that individual-level data can be shared with third-party recommenders. There are many examples of high-quality recent research conducted using appropriately anonymized, individual-level data that are compliant with HIPAA. Based on this, we believe that sufficient anonymization can be achieved to support the proposal we outline.

- If data feeds take a long time to move from an insurer to the centralized data repository, data might not be recent enough, leading to worse recommendations or choice predictions. While there is value in rapidly updating data, the need to choose a health plan is reasonably infrequent, and when combined with widely available retrospective data to support decision making and smart default tools, this issue is unlikely to be a major problem. However, any ability to facilitate more-rapid and up-to-date individual health data will enhance any of the tools we discuss.

Chapter 6. Conclusion

This policy proposal has outlined a set of two key elements designed to enhance the function of insurance markets on exchanges. The target for these proposed changes are regulators and exchange operators across a variety of settings. We believe these changes would enhance consumer welfare—through cost reductions and improved insurance coverage—in Medicare, on ACA exchanges, and in private exchanges and employer-based settings with choice. That said, our primary focus is on publicly provided choice settings (e.g., Medicare, HealthCare.gov, and state-based exchanges).

We believe that (i) providing personalized decisions support and, in some cases, (ii) implementing a smart default policy will accomplish key policy goals. Specifically, we believe that consumers will pay less for insurance coverage and obtain better coverage among existing insurance offerings. Furthermore, innovation in insurance benefit design that provides real consumer value will result, leading to long-run market improvements. Simultaneously, the public budget impact of providing health insurance—a major component of state and federal budgets—can be substantially reduced.

Appendix A. Supporting Material for Choice Simulation

SETUP

To illustrate the benefits and trade-offs associated with a smart default policy, we construct a simple simulation in the form of a case study. We consider a patient from a given age, gender, and location who must select between three health insurance plans, each offered in two provider networks. Based on actual offerings by major insurers, we suppose that this individual faces the plan options described in table 5, all with an out-of-pocket maximum of $6,250.

TABLE 5.

Simulated Health Insurance Options

Plan Option	Deductible	Coinsurance	Network 1 Monthly Premium	Network 2 Monthly Premium
Bronze 60	$4,500	40%	$214	$221
Silver 70	$2,000	20%	$293	$272
Gold 80	$0	20%	$363	$375

We then simulate cost-of-care data for 10,000 of such individuals based on a logarithmic distribution of annual health-care expenditures approximating those of the age, gender, and location group assumed above. Simulated average annual out-of-pocket expenditures for each plan conform fairly closely to stated actuarial values (within 2.5 percentage points for each plan).

PLAN VALUE

We calculate individuals' values for each plan using their expected out-of-pocket expenditures for the year, annual premiums, and a simulated preference for one network over another. We assume that preferences are normally distributed and that the average consumer has no preference between the two networks. A consumer with preferences one standard deviation above the mean would be willing to pay an additional $20 per month to enroll in their preferred network. We then assume that individuals have on average moderate levels of risk aversion with moderate heterogeneity across the simulated sample (constant absolute risk aversion utility with coefficient of risk aversion mean .0006, standard deviation .0008). To determine relative plan values, we calculate the difference in certainty equivalent between the selected plan and the lowest-valued plan offered.

FRICTIONS

The motivation for this exercise is that consumers may face imperfect information, inertia, or other frictions that lead them to make suboptimal health plan choices that do not maximize their plan value. We assume that each individual has a friction value for each plan, drawn randomly from a normal distribution with mean zero and standard deviation of $1,800. This means that, on average, consumers overestimate or underestimate their true value of a given plan by $150 monthly.

COMPARING SMART DEFAULT POLICIES

Out-of-pocket expenditures average $3,049, $2,193, and $1,293 for bronze, silver, and gold plans, respectively. If a default policy were to do nothing but default a patient of this demographic into the optimal plan for the average patient (having information only on age, gender, and state of residence), it would save her around 4 percent of her annual premium per year. In this case, the gold plan from the Network 1 plan would be the default plan for this group using only demographic information, as it the best option for around 47.5 percent of consumers. If the regulators were able to use past claims data to better predict expected health costs, the consumer could save 5.7 percent of her yearly premiums, on average, by participating in the default tailored plan. This assumes that the regulators are able to project expected health costs with a standard deviation of $300 around true expected costs. However, additional data also make it possible to implement a less-aggressive smart default policy, which defaults patients away from their chosen plan only if projected benefits surpass a set amount. In this simulation, a less-aggressive smart default policy would increase welfare on average while harming virtually none of the patients who are defaulted away from their chosen policy. For example, defaulting a patient to a new policy only if her projected benefit exceeds $400 results in an average benefit of 4.1 percent of annual premiums while causing only 5.6 percent of the sample to be defaulted to a less ideal plan than the one she had previously chosen.

Authors

Ben Handel

Assistant Professor of Economics, University of California, Berkeley

Ben Handel is an Assistant Professor of Economics at the University of California at Berkeley and Faculty Research Fellow at the National Bureau of Economic Research (NBER). He is a 2015 Alfred P. Sloan Research Fellow in Economics and participated in the 2010 Review of Economics Studies European Tour. His research focuses on the microeconomics of consumer choice and market structure in the health care sector, with an emphasis on health insurance markets. His most recent research has emphasized the important role that consumer choice frictions, such as inertia and limited information, can have when assessing the welfare outcomes of different regulatory policies in health insurance markets. In addition, his work studies incentive design and adoption of information technology by medical providers. Dr. Handel has partnered with a range of large firms and policy organizations in the health care sector to study questions in these areas. He completed his Ph.D. in economics from Northwestern University in 2010, and completed a postdoctoral fellowship with the Robert Wood Johnson Foundation in 2011. He received an A.B. in economics from Princeton University in 2004.

Jonathan Kolstad

Assistant Professor of Economic Analysis and Policy, Haas School of Business, University of California, Berkeley

Professor Kolstad is an Assistant Professor of Economic Analysis and Policy at the Haas School of Business at UC Berkeley and a Faculty Research Fellow at the National Bureau of Economic Research. He is an economist whose research interests lie at the intersection of health economics, industrial organization and public economics. In recent research he has studied consumer decision making in insurance markets, the value of information feedback to physicians in enhancing health care quality and the impact of many key elements of the Affordable Care Act (ACA) on health care delivery, insurance markets and wages and employment, using the Massachusetts experience as a natural experiment. Kolstad was awarded the Arrow Award from the International Health Economics Association for the best paper in health economics in 2014. Professor Kolstad is also a co-founder and Chief Data Scientist at Picwell Inc. Professor Kolstad received his PhD from Harvard University and BA from Stanford University.

Acknowledgements

We thank The Hamilton Project team for their assistance and insight in creating this proposal, especially Melissa Kearney, Jane Dokko, Gregory Nantz, and Diane Whitmore Schanzenbach. We also thank Allyson Barnett and Grant Graziani of the University of California at Berkeley for their excellent research assistance in preparing material for this proposal. In addition, we benefited greatly from the comments we received on the proposal from participants at The Hamilton Project authors' conference held at Brookings in June 2015. We thank numerous collaborators and fellow researchers who have helped to create and hone different ideas related to this proposal. Both authors are employees of Picwell Inc. The views herein reflect those of the authors alone.

Endnotes

1. Statutory language: "(b) AMERICAN HEALTH BENEFIT EXCHANGES.—(1) IN GENERAL.—Each State shall, not later than January 1, 2014, establish an American Health Benefit Exchange (referred to in this title as an "Exchange") for the State that—(A) facilitates the purchase of qualified health plans."
2. CMS is currently making strides in providing deidentified access to Medicare claims, but the private claims data that are necessary to support non-Medicare exchanges remain far behind. Even the current CMS data provision policy limits access for private firms, resulting in tools developed by only a handful of entrenched players. Given the existing decision support, this has clearly not yielded the level of innovation necessary to overcome choice errors in the Medicare market.
3. Though providing a breakdown is an option, to overcome the kinds of choice errors we document above in which people weight different cost components differently even though they all represent actual dollars spent, a total out-of-pocket assessment can be highly effective.
4. In the context of the data infrastructure, it is likely that an effective smart default policy will require (i) detailed plan design information, (ii) detailed plan network information, and (iii) at least some individual-specific health data, either administrative- or user-provided. We go on to discuss how smart default policies can be adjusted as a function of the strength and limitations of a given exchange's data environment. Generally speaking, as data become deeper and better integrated, more-aggressive smart default policies are possible. As discussed in box 2, there are certainly rich enough data environments in exchanges that exist today for smart defaults to be actively considered.
5. To be clear, an individual can be made worse off by a smart default if the algorithm used to make the assignment does not capture her individual specific situation with sufficient granularity and she does not actively change to a better option. In any setting that relies on prediction there will be some measurement error (e.g., Amazon frequently recommends products that no one actually wants). In our setting, this is manifest in realization of health events that make the plan worse for an individual even though, given everything known when the choice was made, that was the best option for her.

References

Abaluck, Jason, and Jonathan Gruber. 2011. "Heterogeneity in Choice Inconsistencies among the Elderly: Evidence from Prescription Drug Plan Choice." *American Economic Review* 101 (3): 377–81.

Abaluck, Jason, and Jonathan Gruber. 2013. "Evolving Choice Inconsistencies in Choice of Prescription Drug Insurance." Working paper 19163, National Bureau of Economic Research, Cambridge, MA.

Bhargava, Saurabh, George Loewenstein, and Justin Sydnor. 2015. "Do Individuals Make Sensible Health Insurance Decisions? Evidence from a Menu with Dominated Options." Working Paper 21160, National Bureau of Economic Research, Cambridge, MA.

Congressional Budget Office (CBO). 2014. "Competition and the Cost of Medicare's Prescription Drug Program." Washington, DC.

Ericson, Keith M. 2014. "Consumer Inertia and Firm Pricing in the Medicare Part D Prescription Drug Insurance Exchange." *American Economic Journal: Economic Policy* 6 (1): 38–64.

Ericson, Keith M., and Amanda Starc. 2013. "How Product Standardization Affects Choice: Evidence from the Massachusetts Health Insurance Exchange." Working paper 19527, National Bureau of Economic Research, Cambridge, MA.

———. 2015. "Pricing Regulation and Imperfect Competition on the Massachusetts Health Insurance Exchange." *Review of Economics and Statistics* 97 (3): 667–82.

Fang, Hanming, Michael P. Keane, and Dan Silverman. 2008. "Sources of Advantageous Selection: Evidence from the Medigap Insurance Market." *Journal of Political Economy* 116 (2): 303–50.

Gobeille v. Liberty Mutual Insurance Co. (2015). SCOTUSblog. http://www.scotusblog.com/case-files/cases/gobeille-v-liberty-mutual-insurance-company/.

Handel, Ben R. 2013. "Adverse Selection and Inertia in Health Insurance Markets: When Nudging Hurts." *American Economic Review* 103 (7): 2643–82.

Handel, Ben R., and Jonathan T. Kolstad. 2015. "Health Insurance for 'Humans': Information Frictions, Plan Choice, and Consumer Welfare." *American Economic Review* 105 (8): 2449–2500.

Health Insurance Portability and Accountability Act of 1996 (HIPAA), Pub. L. 104-191, 110 Stat. 1936 (1996).

Heiss, Florian, Daniel McFadden, and Joachim Winter. 2010. "Mind the Gap! Consumer Perceptions and Choices of Medicare Part D Prescription Drug Plans." In *Research Findings in the Economics of Aging*, edited by David A. Wise, 413–81. Chicago: University of Chicago Press.

Ho, Katherine. 2009. "Insurer-Provider Networks in the Medical Care Market." *American Economic Review* 99 (1): 393–430.

Ho, Katherine, Joseph Hogan, and Fiona Scott Morton. 2015. "The Impact of Consumer Inattention on Insurer Pricing in the Medicare Part D Program." Working paper 21028, National Bureau of Economic Research, Cambridge, MA.

Ketcham, Jonathan D., Claudio Lucarelli, Eugenio J. Miravete, and M. Christopher Roebuck. 2012. "Sinking, Swimming, or Learning to Swim in Medicare Part D." *American Economic Review* 102 (6): 2639–73.

Ketcham, Jonathan D., Claudio Lucarelli, and Christopher A. Powers. 2015. "Paying Attention or Paying Too Much in Medicare Part D." *American Economic Review* 105 (1): 204–33.

Kling, Jeffrey R., Sendhil Mullainathan, Eldar Shafir, Lee C. Vermeulen, and Marian V. Wrobel. 2012. "Comparison Friction: Experimental Evidence from Medicare Drug Plans." *Quarterly Journal of Economics* 127 (1): 199–235.

Lazer, David, Ryan Kennedy, Gary King, and Alessandro Vespignani. 2014. "The Parable of Google Flu: Traps in Big Data Analysis." *Science* 343 (14 March).

Madrian, Brigitte nd Dennis Shea. 2001. "The Power of Suggestion: Inertia in 401(k) Participation and Savings Behavior." *Quarterly Journal of Economics* 116:4.

Marton, James, Aaron Yelowitz, and Jeffrey C. Talbert. 2015. "Medicaid Program Choice and Participant Inertia."Working Paper, University of Kentucky.

Medicare Prescription Drug, Improvement, and Modernization Act of 2003, Pub. L. 108-173.

Polyakova, Maria. 2014, August 31. "Regulation of Insurance with Adverse Selection and Switching Costs: Evidence from Medicare Part D." Paper 2536530, Social Science Research Network, Rochester, NY.

Porter, Michael E., and Elizabeth O. Teisberg. 2006. *Redefining Health Care: Creating Value-Based Competition on Results*. Harvard Business School Press, Cambridge, MA.

Strombom, Bruce A., Thomas C. Buchmueller, and Paul J. Feldstein. 2002. "Switching Costs, Price Sensitivity and Health Plan Choice." *Journal of Health Economics* 21 (1): 89–116.

Thaler, Richard H., and Sunstein, Cass R. 2008. *Nudge*. New Haven, CT: Yale University Press.

Zhang, Yuting, Chao Zhou, and Seo Hyun Baik. 2014. "A Simple Change to Medicare Part D's Low-Income Subsidy Program Could Save $5 Billion." *Health Affairs* 33 (6): 940–45.

THE HAMILTON PROJECT

ADVISORY COUNCIL

Highlights

There is substantial evidence of consumers miscalculating their health and financial risks when choosing health insurance, which often results in extra costs that can run into the hundreds of dollars. Evidence also documents consumers remaining in their selected health insurance plans, even as better and more cost-effective options become available. In addition, since federal and state governments often subsidize private health insurance, public outlays are much higher than they need to be. Ben Handel and Jonathan Kolstad of the University of California, Berkeley, offer two proposals to help consumers select the health insurance plan that is cost-effective and best aligns with their needs. They focus on those individuals enrolled in the federal and state-run insurance exchanges, including the ACA exchanges, Medicare Part D, and Medicare Advantage.

The Proposals

Introduce a Decision Support Tool with Personalized Recommendations. This tool would incorporate an individualized cost calculator, an assessment of risk, hospital and physician network information, and individual preferences.

Institute Smart Defaults. The exchange regulator would switch consumers from their current plan to a new plan if the new plan offered more value, minimal new risk exposure, and continuity of covered providers. Consumers would maintain the ability to switch out of the smart default plan to retain their current coverage or to select a different plan.

Benefits

These proposals would benefit the consumer, helping her to save up to hundreds of dollars each year. Federal and state governments could also save billions of dollars from the reduction in subsidies that results from better matches between consumers and their insurance plans.

THE HAMILTON PROJECT

1775 Massachusetts Ave., NW
Washington, DC 20036

(202) 797-6484

BROOKINGS

Printed on recycled paper.

WWW.HAMILTONPROJECT.ORG