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Essays on Industrial Organization and Health Economics

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Abstract

My thesis consists of three chapters studying the impact of health insurance design and public health policy on consumers' health and health care utilization, welfare, and costs.

Chapter 2 studies an overlooked dynamic incentive that encourages health care utilization, which I term *dynamic moral hazard*. Typical health plans feature high deductibles and caps on consumers' out-of-pocket spending, which generate nonlinear pricing. These nonlinearities, coupled with the uncertainty intrinsic to future health care demand, encourage consumers to increase spending since current utilization lowers future expected prices. Standard models study health care utilization decisions through the lens of annual models, which abstract from the dynamic incentives throughout the year induced by nonlinear pricing. To understand the implications of dynamic moral hazard on insurance design, I develop and estimate a dynamic, within-year model of health care demand that allows for rich, flexibly-correlated unobserved heterogeneity. I use this model to study alternative contract designs in the context of employer-sponsored health insurance. My results show that the presence of dynamic moral hazard can severely dampen the welfare gains associated with higher cost-sharing and plays a crucial role, distinct from static moral hazard, in determining optimal insurance contract design.

Motivated by the substantial unobserved heterogeneity found in Chapter 2, Chapter 3 studies the evidence for and sources of selection, both adverse and advantageous. I first propose a new method to recover family-specific distributions of multidimensional unobserved heterogeneity conditional on their health care utilization decisions and the estimated population distribution of types. Using insurance choice survey data and the model from Chapter 2, I recover family-specific measures of risk aversion. Finally, I examine the correlation between risk aversion and the other dimensions of unobserved heterogeneity to unmask potential sources of advantageous selection. I find a new source of advantageous selection: preferences for going to the doctor, which suggests advantageous selection on number of visits instead of health. These findings have implications for the plan portfolio choice problem and suggest that models with richer unobserved heterogeneity might capture the gains from offering plan choice.

The first two chapters focus on studying health care demand for insured people. However, an important fraction of the population does not have health insurance and relies on the health care safety net to get needed care. Chapter 4 estimates the causal impact of a maternity conditional cash transfer program on the choice between abortion and childbirth in a context where abortion is illegal. We leverage several sources of social security administrative micro-data matched to longitudinal hospital records to estimate the effect of participating in the Argentinean *Asignación por Embarazo para Protección Social*, a conditional cash transfer program implemented in 2011 and targeted at pregnant women who are unemployed or working in the informal sector. We exploit the substantial amount of inflation in Argentina to instrument for endogenous participation in the program. We estimate that participation in the program led to a sizable reduction in the probability of abortion and in the incidence of normal birthweight. These findings are consistent with a change in composition effect, in which mothers whose abortion decision is affected have a higher risk of low birthweight children.

Keywords: Nonlinear health insurance, dynamic moral hazard, advantageous selection, conditional cash transfer programs, abortion and birthweight

Summary for Lay Audience

My thesis consists of three chapters studying the impact of health insurance design and public health policy on consumers' health and health care utilization, welfare, and costs.

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Co-Authorship Statement

This thesis contains material co-authored with Timothy G. Conley. All the authors are equally responsible for the work which appears in Chapter 4 of this thesis.

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To my late mother, Gladys Patricia

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Chapter 1

Introduction

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In Chapter 2, I study optimal contract design in the context of employer-sponsored health insurance, where the employer offers only one plan and everyone takes that plan. A natural extension involves optimal menu design: whether and how the employer should offer plan choice. The study of the plan portfolio choice problem by the firm is highly impacted by the degree and nature of selection. Motivated by the substantial amount of unobserved heterogeneity found in the previous chapter, Chapter 3 studies the evidence for and sources of selection, both adverse and advantageous. I first propose a new method to recover family-specific distributions of multidimensional unobserved heterogeneity conditional on their health care utilization decisions and the estimated population distribution of types. I complement the health care utilization data with survey data on families' responses to hypothetical offers to purchase supplementary insurance coverage. Using these insurance choice data and the dynamic structural model from the previous chapter, I recover family-specific measures of risk aversion. Finally, I examine

the correlation between risk aversion and the other dimensions of unobserved heterogeneity to unmask potential sources of advantageous selection. According to my results, more risk-averse people are not particularly healthy. Moreover, I find evidence of a new potential source of advantageous selection: preferences for visiting the doctor. These two findings together would suggest that advantageous selection works through fewer doctor visits as opposed to better health. I also document substantial selection on moral hazard, suggesting people choose plans in part based on their anticipated response to more generous insurance. My results have important implications for thinking about optimal plan portfolio choice and suggest that inadequately measuring the extent and correlation between multidimensional private information might lead to optimal menus that feature a single plan.

Chapters 2 and 3 focus on studying health care demand for insured people. However, an important fraction of the population does not have health insurance and relies on the health care safety net to get needed care. This scenario is even more prevalent in developing countries, where the safety net is comprised of basic and usually poorly-run public hospitals. Chapter 4, written in co-authorship with Timothy G. Conley, estimates the causal impact of a maternity conditional cash transfer program on the choice between abortion and childbirth in a context where abortion is illegal. We leverage several sources of social security administrative micro-data matched to longitudinal hospital records to estimate the effect of participating in the Argentinean *Asignación por Embarazo para Protección Social*, a conditional cash transfer program implemented in 2011 and targeted to pregnant women who are unemployed or working in the informal sector. The main objective of the program is to reduce maternal, perinatal, neonatal, and infant mortality rates that are associated with problems in access to timely health services. We exploit the substantial amount of inflation in Argentina to instrument for the endogenous participation in the program. We estimate that participation in the program led to a sizable reduction in the incidence of abortion while increasing the probability of low birthweight. Our findings are consistent with a change in composition effect, in which poorer and more disadvantaged women who would have aborted in the absence of the program, decide now to continue their pregnancy but exhibit worse health outcomes.

Chapter 2

Dynamic Moral Hazard in Nonlinear Health Insurance Contracts

2.1 Introduction

Typical health insurance contracts increasingly include sizable annual deductibles and caps on consumers' out-of-pocket expenditures. In the context of employer-sponsored health insurance in the United States, 83 percent of covered workers had a deductible in 2020 and all had a plan with a cap on out-of-pocket expenditures.[1] The presence of deductibles and caps give rise to nonlinear health insurance contracts, where the out-of-pocket price decreases as the cumulative use of health care (over the covered year) increases. In a typical nonlinear contract, families pay the full price of care below the deductible. After the deductible is exhausted, families pay only a portion of the bill equal to the coinsurance rate, and, once they reach the cap, they face no cost-sharing and have complete insurance coverage for the remainder of the year. These nonlinear benefit structures, coupled with the uncertainty surrounding future health care demand, create dynamic incentives for consumers because current health care utilization reduces future expected prices.

Standard analyses of insurance contracts study the trade-off between the welfare gains from risk protection and the welfare losses when consumers do not face the full cost of their care (Arrow, 1963; Pauly, 1968). In the health insurance literature, the term "moral hazard", which I relabel as *static moral hazard*, is used to capture the notion that insurance coverage may increase health care use by lowering the out-of-pocket price of care to the individual (Einav and Finkelstein, 2018).[2] In this paper, I study a new source of moral hazard, *dynamic moral*

[1] These numbers are up from 70 percent and 82 percent a decade ago, respectively. Source: Employer Health Benefits Survey 2020, Kaiser Family Foundation.

[2] As emphasized by Einav and Finkelstein (2018), the use of the term "moral hazard" is an abuse of the

hazard, which I define as the extra health care utilization when individuals internalize that the more they consume today, the closer they move towards the deductible and the cap, and the higher the probability they enjoy lower prices for the remainder of the year. Thus, an additional benefit of health care utilization today is lower future expected out-of-pocket prices.

The presence of dynamic moral hazard has implications for the standard analysis of moral hazard. For example, a standard approach to reducing moral hazard is to increase consumer cost sharing. But, if individuals anticipate a lower future price, they respond to a shadow price lower than the spot price in the range below the deductible. Thus, much of the savings thought-to-be-achieved in this range will not actually be realized. Given the concern about the size and rapid growth of the health care sector, there is considerable academic and public policy interest in a better understanding of moral hazard and the ways to mitigate its impact on social welfare. Dynamic moral hazard is particularly relevant in this context, because nonlinear contracts are widely popular not only in private health insurance but also, increasingly, in public health insurance programs, such as Medicare Part D.

Recognition of the possibility of dynamic moral hazard highlights potentially important limitations of standard models of health insurance that have traditionally overlooked these dynamic incentives and their implications in health insurance.[3] Most empirical papers study health care utilization decisions through the lens of annual models, which aggregate health care decisions up to the annual level (see e.g., Einav, Finkelstein, Ryan, Schrimpf, and Cullen (2013), Kowalski (2015), Ho and Lee (2020), and Marone and Sabety (2022)). In these models, individuals make a one-shot decision under full certainty about the complete sequence of health shocks within the year. If future health care demand could be predicted with certainty, the sequential decision problem would be the same as in the one-period case. When uncertainty is present, any health care utilization in the range below the cap has the additional benefit of reducing the remaining cap and, hence, reducing the expected costs of future health care. Annual models thus abstract, by design, from the uncertainty intrinsic to health care demand and the dynamic incentives induced by the nonlinearities of the contracts, which could have important implications in health insurance design. This limitation is not unique to annual models of health care utilization.[4]

"hidden action" origin of the term. In the health insurance literature, the "action", i.e., the agent's health care utilization decision, is observed and contractible. The asymmetric information problem may be more accurately described as a problem of "hidden information" regarding the agent's health risk.

[3]Two exceptions are the early theoretical works of Keeler, Newhouse, and Phelps (1977) and Ellis (1986). Empirically, Cronin (2019) allows the nonlinearities of the contract to affect the number of monthly health care visits, but not the dollar amount consumed. Similarly, in Einav, Finkelstein, and Schrimpf (2015) individuals decide weekly whether to fill a prescription drug, internalizing the impact on expected future prices. None of these papers quantifies dynamic moral hazard and its implications for the design of health insurance contracts.

[4]More broadly, the dynamic pricing incentives are neglected whenever the frequency of the consumer's de-

In this paper, I begin by providing compelling evidence showing that consumers respond to the dynamic incentives of nonlinear contracts and I explore the nature of this response. I then use my findings to develop a tractable, within-year model of health care demand that incorporates the dynamic pricing effects via the nonlinearities of the contract. I estimate the model primitives using a state-of-the-art technique that allows for multidimensional, flexibly-correlated unobserved heterogeneity in health risks, preferences for doctor visits, and price sensitivity. Finally, I use my model and estimates to study the implications of dynamic moral hazard for the optimal design of nonlinear contracts in the context of employer-sponsored health insurance. To do so, I explore the interplay between four contract features: (1) the deductible size, (2) the coinsurance rate after the deductible, (3) the cap on out-of-pocket expenditures, and (4) the resetting time for deductibles and caps. While the first three features are standard in the literature, the optimal resetting time for deductibles and caps has not been studied before.[5]

I use rich, individual, line-item records from the RAND Health Insurance Experiment (Newhouse and The Insurance Experiment Group, 1993). The RAND experiment is a large randomized field trial of alternative insurance plans offered to approximately 2,500 families representing the non-elderly U.S. population. The experiment randomly assigned families to one of 14 different fee-for-service insurance plans that varied along two principal dimensions: the coinsurance rate and the annual cap on out-of-pocket expenditures. By leveraging the random assignment of families to plans, I can focus on the problem of moral hazard, avoiding the typically confounding adverse selection present in insurance markets (Akerlof, 1970).[6]

To provide evidence of whether consumers internalize the dynamic incentives induced by typical health insurance contracts, I first derive four testable implications within a linear regression of weekly health care utilization on cumulative utilization (over the coverage year), contract week, and their interaction. Using family fixed effects, I exploit the within-family variation in the shadow price of care that comes from two different sources: the distance to the cap on out-of-pocket expenditures and the number of weeks left in the contract before the price

cision in the model coincides with the length of the contract or when the individuals' behavior is assumed to respond only to the spot price of care.

[5]I recently became aware of the concurrent work of Hong and Mommaerts (2021), which explores the implications of deductibles that reset over 6 months versus 12 months. There is also a parallel between the early theoretical work of Keeler, Relles, and Rolph (1977) analyzing individual versus family deductibles has a parallel with the optimal resetting time for deductibles. A separate literature studies the optimal *contract* length (and therefore the optimal frequency of open enrollment), holding the timespan over which deductibles and OOP limits aggregate to be annual. See e.g., Darmouni and Zeltzer (2017) in health care, Ghili, Handel, Hendel, and Whinston (2020) and Atal, Fang, Karlsson, and Ziebarth (2020) in long-term care, and Cabral (2016) in dental care.

[6]Because of their nonlinear cost-sharing features, the RAND plans anticipated the design of modern health insurance plans and still receive much theoretical and empirical attention (see e.g., Lin and Sacks (2019), Aron-Dine, Einav, Finkelstein, and Cullen (2015), and Vera-Hernandez (2003)).

schedule resets. I also leverage the staggered enrollment dates from the experimental design to separate seasonal variation in health care demand from the dynamics of my model. Intuitively, the first two implications capture that the further away from the cap and the closer to the end of the contract, the lower is the likelihood of reaching the cap before the contract resets, which increases the shadow price and discourages current utilization. The last two implications check that none of the first two effects survive once families exceed their cap. Using two measures of health care utilization, I show that the implications hold, suggesting that the observed behavior is consistent with forward-looking families who internalize the dynamic pricing effects by updating their expected future prices over the course of the year.

Informed by this evidence, I build a single-agent, finite-horizon, dynamic, stochastic model of health care utilization at the family level combining elements of the annual model of health care demand from Einav, Finkelstein, Ryan, Schrimpf, and Cullen (2013) and the within-year model of internet demand from Nevo, Turner, and Williams (2016). I model families' health care utilization decisions at the weekly level where they respond to the *shadow* (or effective) price of health care, rather than the *spot* price or the realized end-of-year price.[7] Thus, families in my model act as though they face a shadow price lower than the spot price in the range below the cap. In line with my regression estimates, the model implies that the shadow price of care is weakly decreasing in the proportion of the cap consumed and in the number of weeks left before the contract resets. In this way the model accounts for the fact that decisions are made sequentially throughout the year and information is obtained gradually as health shocks arrive and families move along their nonlinear budget set.

I then estimate my model by adapting the approach proposed by Ackerberg (2009), Bajari, Fox, and Ryan (2007), Fox, Kim, Ryan, and Bajari (2011), and Fox, Kim, and Yang (2016); and recently applied by Nevo, Turner, and Williams (2016) in the context of demand for residential broadband and Blundell, Gowrisankaran, and Langer (2020) in firms' investment decisions in pollution abatement technologies. This approach allows me to incorporate flexibly-correlated unobserved heterogeneity in four dimensions related to family health risk (two dimensions), preferences for visiting the doctor, and price sensitivity, and a fifth partially-observed dimension that captures family income. The existence of multiple dimensions of individuals' private information is well documented in the literature (see e.g., Finkelstein and McGarry (2006) in the long-term care insurance market and Fang, Keane, and Silverman (2008) in the Medi-

[7] In general, nonlinear cost-sharing features of health insurance contracts imply that the out-of-pocket price of health care declines as total utilization accumulates. Thus, at any point in time, the *shadow* price of a unit of health care is the marginal (or *spot*) price minus the bonus for moving closer to the next kink in the budget set, past which cost-sharing by the individual falls or is even eliminated. There are some exceptions. In the case of Medicare Part D, where the coinsurance rates faced by the patients are not monotonically decreasing as total health care utilization accumulates, the *shadow* price can potentially exceed the *spot* price of care.

gap insurance market). Nevertheless, previous literature has been constrained regarding the amount of heterogeneity they could allow for and their correlation structure, mainly due to computational reasons. I overcome these constraints by using the computationally advantageous estimator of Fox, Kim, Ryan, and Bajari (2011).

The estimator recovers the nonparametric distribution of unobserved heterogeneity using inequality constrained least squares on a fixed grid. While applying the method of Fox, Kim, Ryan, and Bajari (2011) helps reducing the computational burden, there is still a curse of dimensionality as the number of dimensions in the grid increases. I determine the grid of family types by adapting the method of good lattice points (*glp*) introduced in economics by Judd (1998) in the context of integration and simulation. Good lattice point sets have better space-filling properties than standard tensor product point grids or random sequences and can produce more accurate approximations. As far as I know, this paper is the first to apply this method to dynamic programming problems. Results from a Monte Carlo exercise suggest that it improves computational efficiency by more than a factor of ten. Fox, Kim, Ryan, and Bajari (2011) approach together with the *glp* method enables me to introduce considerable unobserved heterogeneity in health care demand.

In order to decompose static moral hazard from dynamic moral hazard, I simulate a version of my model in which families are myopic, and thus do not respond to the dynamic price incentives. In this model, families respond only to the current spot price of care. I document that 40 percent of total moral hazard is attributed to the dynamic moral hazard component, whereas the rest is standard moral hazard. Moreover, I find that certain contract features exacerbate the impact of dynamic moral hazard on utilization. This highlights the importance of accounting for the dynamic pricing effect when thinking about the optimal cost-sharing features in health insurance.

To analyze the impact of dynamic moral hazard on welfare, I extend the welfare decomposition of Azevedo and Gottlieb (2017) and Marone and Sabety (2022) and provide a novel decomposition in three terms: the value of risk protection, the social cost of static moral hazard, and the social cost of dynamic moral hazard. Using full insurance as a benchmark, I study the impact of dynamic moral hazard on welfare under alternative contract designs not observed in the data. First, I find that for low caps dynamic moral hazard is particularly strong. So while welfare losses from higher caps due to risk protection are also increasing with the cap, the presence of dynamic moral hazard implies larger optimal caps than would be predicted otherwise. Second, zero deductibles are optimal for low caps, but high deductibles are welfare-maximizing for high caps. In other words, what matters is the distance between the deductible and the cap. So while a high deductible increases the gains due to static moral hazard, a de-

ductible too close to the cap exacerbates the losses due to dynamic moral hazard. This implies, for example, that pure stop-loss contracts in which the deductible and the cap coincide are never optimal. Finally, I find that longer resetting times increase the probability of hitting the cap at some point during the coverage period, so resetting times shorter than twelve months are welfare-maximizing.

Beyond the work noted above, my paper relates to several strands of literature. First, it adds to the sparse literature that test whether individuals respond to the within-year dynamic incentives induced by nonlinear health insurance contracts.[8] The closest to my paper is Aron-Dine, Einav, Finkelstein, and Cullen (2015) which exploits quasi-experimental variation due to timing of new hires enrolling in employer-provided health insurance plans. The focus on dynamic incentives relates more generally to empirical tests of forward-looking behavior, which plays a key role in many economic problems. Outside the context of health insurance, two works related to mine are Nevo, Turner, and Williams (2016) who analyze the effect of nonlinear pricing schedules in the context of residential broadband use, and Chevalier and Goolsbee (2009) who investigate whether durable goods consumers are forward looking in their demand for college textbooks.

Second, my paper is one of the very few empirical papers which considers health care utilization decisions for periods shorter than the standard contract length of twelve months. By doing so, I incorporate the uncertainty intrinsic to the nature of health care demand and the dynamic incentives throughout the year induced by the nonlinear pricing of typical health insurance contracts. I also model explicitly how health care utilization decisions change with the number of periods left until the contract resets. Thus, I leverage my structural model to explore contracts with shorter resetting times for deductibles and caps, their impact on welfare, and the unique role played by dynamic moral hazard.

My paper also relates to the literature that studies optimal design of health insurance contracts emphasizing the trade-off between welfare gains from risk protection and welfare losses from moral hazard. My paper is closest in spirit to the work of Kowalski (2015), Ho and Lee (2020), and Marone and Sabety (2022), which propose a coherent and unified framework to evaluate risk protection and moral hazard simultaneously. However, none of these papers study the dynamic moral hazard component and its policy implications. Finally, my paper adds to the methodological literature for estimating demand under rich and flexibly-correlated multidimensional unobserved heterogeneity by adapting the methodology from Fox, Kim, Ryan, and Bajari (2011) and Nevo, Turner, and Williams (2016), combined with the use of good lattice

[8] See e.g., Aron-Dine, Einav, Finkelstein, and Cullen (2015), Einav, Finkelstein, and Schrimpf (2015), Keeler and Rolph (1988), and Guo and Zhang (2019).

points.

The remainder of the paper proceeds as follows. Section 2.2 describes the data and Section 2.3 presents descriptive evidence of responses to the shadow price variation. Section 2.4 details the dynamic model of weekly health care utilization. In Section 2.5, I present the econometric specification of my model and describe its estimation and identification. Section 2.6 presents the main results. Section 2.7 examines optimal contract design within the setting of employer-sponsored health insurance. The last section concludes.

2.2 Data and Sample

I use rich, individual, line-item records from the RAND Health Insurance Experiment (hereafter, HIE). The RAND HIE is a randomized field trial of alternative insurance plans offered to approximately 2,500 non-elderly families in the U.S. Each line-item record contains information on the total line-item cost, out-of-pocket expenses, insurance payment, date and place of service, and procedure codes. The data are particularly suitable for the study of moral hazard because insurance plans were randomly assigned to families. This forestalls the possibility that less-healthy people, anticipating large health care expenditures, buy more generous insurance coverage (Akerlof, 1970). Specifically, these data are ideal for studying dynamic moral hazard given the unique cross-randomization design of nonlinear cost-sharing features. In what follows I describe the experimental design and the analysis sample.

2.2.1 Experimental design and randomization

The RAND HIE is a large social experiment conducted between 1974 and 1982 in four urban and two rural sites, chosen to be broadly representative of the nonelderly U.S. population.[9] Families offered enrollment in the experiment represent a random sample from each site, subject to certain eligibility criteria. The criteria excluded those whose health care delivery systems differed from options available to the general population.[10] At a given site and enrollment date, families were randomly assigned to one of 14 different fee-for-service insurance plans or

[9]The sites were: Dayton, Ohio; Seattle, Washington; Fitchbury-Leominster and Franklin County, Massachusetts; and Charleston and Georgetown County, South Carolina.

[10]The experiment excluded people age 62 or over at the time of enrollment since they were or would become eligible for Medicare during the experiment or people under age 62 who were eligible for the Medicare program; those with family incomes greater than $25,000 (in 1973 dollars); those who were institutionalized (jail or long-term hospital); those in the military and their dependents; and veterans with service-connected disabilities.

to a prepaid group practice.[11] In addition, each family was randomly assigned to either three or five years of participation. Families were enrolled in the experiment as a unit, with only eligible family members participating.[12]

The fee-for-service plans varied along two principal features: (1) the coinsurance rate, which is the fraction of billed charges paid by the participant, and (2) the maximum dollar expenditure (MDE), which is the cap on family out-of-pocket expenditures. The coinsurance rates were set at either 0 (free care), 25, 50, or 95 percent. Except for the free care plan, each plan had a MDE of 5, 10, or 15 percent of family income in the previous year (hereafter, PY).[13] To further limit participants' financial exposure, the MDE was capped at $1,000 in 1973 dollars, unadjusted for inflation.[14] Beyond the MDE, the insurance plan paid all covered health care utilization in full for the remainder of the contract year. Associated with the MDE, it will become useful to introduce the concept of a Total Annual Threshold (hereafter, TAT), defined as the ceiling placed on accumulated health care utilization during the coverage period above which health care is free to the family members. The TAT differs from the MDE because the former includes both the portion paid by the insurance and the portion paid out-of-pocket by the patient, while the latter only includes the patient's portion.

All experimental plans feature a zero-dollar deductible, a coverage length of 12 months, and no premiums. Every plan covered inpatient and outpatient health care, as well as vision, prescription drugs, medical supplies, and mental and dental health.[15] A contract year was defined as the 12-month period following each anniversary of the enrollment date, which was not always January 1. New families were enrolled over several start dates, but all members of

[11] The RAND HIE assigned families to treatments using the Finite Selection Model (Morris et al., 1979), which explicitly balanced a subset of observable characteristics across plans. Potential selection bias can be introduced if there is differential refusal or attrition across plans. To reduce refusals, families were given a Participation Incentive (PI) if their experimental plans provided less coverage than their existing health insurance policies. For details about the PI payments see Appendix A of Codebook 203 (Newhouse, 1999). A Completion Bonus was offered to reduce withdrawal from the experiment subsequent to enrollment.

[12] After the enrollment date, families could not incorporate new members into the insurance plan. The only exceptions were newborns and adopted children under one year of age. Families who either lost or acquired members during a given contract year were given a new identifier in the following contract year to reflect their change in composition. Hence, a RAND HIE participant might belong to different families throughout the experiment.

[13] There was a group of mixed plans, in which the coinsurance rate differed between medical services and dental or outpatient psychiatric services. Regarding the MDE, one plan limited the out-of-pocket expenditure to either $150 (individual) or $450 (family). These plans are not analyzed in the present study. Since the MDE is tied to the family's previous year's income, it varied from year to year. Families with zero income in the previous year received *de facto* free care, regardless of the plan.

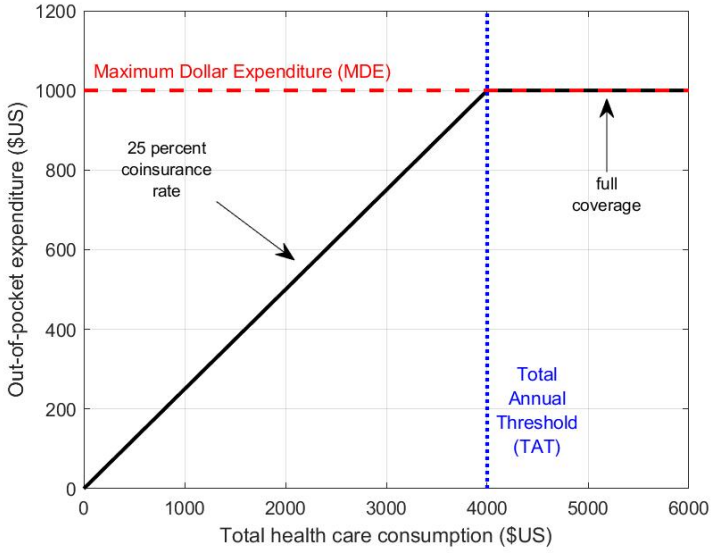
[14] An MDE of $1,000 in 1973 dollars would correspond to about $6,000 in 2020 dollars, based on the U.S. Consumer Price Index (CPI-U). Source: U.S. Bureau of Labor Statistics.

[15] The following services were excluded: non-preventive orthodontic services, cosmetic surgery for pre-existing conditions, and outpatient mental health visits exceeding 52 per contract year. See Appendix D of Codebook 203 (Newhouse, 1999) for a thorough list of possible reasons for noncoverage of a service by the RAND HIE.

a given family shared the same enrollment date, even those added later.[16]

Figure 2.1 shows an example of a health insurance plan offered by the RAND HIE. The total dollar amount of annual health care utilization is summarized on the horizontal axis, as the sum of both insurer payments and out-of-pocket payments by the beneficiary family. The vertical axis indicates how this particular insurance contract translates total utilization into out-of-pocket spending. The figure illustrates the case of a family assigned to a 25 percent coinsurance rate plan with a MDE equals to 10 percent of PY income. Since family income in the previous year is greater than $10,000, the MDE is capped at $1,000 (the horizontal red dashed line). In this case, the family would pay 25 percent of the first $4,000 in health care utilization, and $0 beyond that for the current contract year. Hence, a 25 percent coinsurance rate coupled with a MDE of $1,000 has an associated TAT of $4,000 (the vertical blue dotted line).

Figure 2.1: Health insurance plan with 25 percent coinsurance rate and MDE=min{0.10 × income, $1,000} for a family with PY income greater than $10,000



Except for the absence of a deductible, Figure 2.1 shows a stylized example of a typical health insurance contract in the U.S. This example shows a concave, piece-wise linear schedule with two "arms." First, the "coinsurance" arm, where the family faces a price of 25 percent for every dollar of health care utilization, and second, the "catastrophic" arm that provides full coverage. While the plans in my data do not include deductibles, the same forces that govern health care utilization behavior below the cap also apply to the deductibles, and allow me to use my estimated model to study behavior under plans with deductibles (see Section 2.7).

[16]Table A.1 in the Appendix shows enrollment dates by site.

2.2.2 Sample

For the purpose of studying family behavior within a contract year, I aggregate health care utilization to the family-week-year level.[17] The variable *date of service* defines whether a line-item claim belongs to one week or another.[18] In addition to the claims data, I use the *eligibility* file to record coverage and family structure, and the *episodes of care* file to recover the family MDE by year. The weekly consumption totals represent only the health care utilization that was covered by the RAND HIE and for which claims were submitted. The weekly covered health care utilization used for the analysis includes both the portion paid out-of-pocket by the family and the portion paid by the insurer. If no family member used covered health care services during a given week-year pair, the utilization value for that family-week-year observation equals zero. Note that observations with zero utilization are kept in the sample.

I make five restrictions to create my baseline sample. First, I exclude fee-for-service plans with different coinsurance rates for different providers (i.e., the so-called mixed plans) and the prepaid group practice.[19] Second, I exclude the first contract year from Dayton, Ohio.[20] Third, I exclude family-year observations in which no member enjoyed coverage for the whole contract year. Fourth, for families reassigned to a different plan after a relocation, I exclude the year of the move as well as the following years. Finally, I exclude family-year observations with missing MDE information.[21] After these exclusions, my baseline sample consists of 2,145 families and 4,763 family-years. Table 2.1 provides details about the remaining sample size after sequentially applying each exclusion criterion.

Table 2.2 provides summary statistics by plan type for the baseline sample. I group the insurance plans into four categories based on the coinsurance rate. In the first panel, I explain the features of the plans. In the second panel, I provide statistics at the annual level as well as a break down by category of expenditure. Finally, in the third panel I present statistics regarding the behavior above the cap. Between 17 and 36 percent of families in the cost-sharing plans hit the TAT in a given year. This is important, as my identification strategy relies on having enough families with a positive probability of exceeding the TAT during the contract year. Families in the less generous plans are more likely to hit the TAT due to the higher cost sharing, but

[17] A week refers to a contract week, as opposed to a calendar week. The same applies to a year.

[18] Each claim has multiple dates, including the admission and discharge dates in case of hospitalization, the date of service and the date filed.

[19] My model does not distinguish between providers of service (e.g., physician versus dentist) or whether the provider belongs to a prepaid group network.

[20] Dental and mental health services were treated differently in the first year of the experiment in Dayton, Ohio. Dental services for adults were covered only on the free-care plan (dental services for children were covered on all plans). Outpatient mental services were not covered.

[21] For details about each exclusion step, see Appendix A.8.

Table 2.1: Analysis sample derivation

Row	Description	Sample Size	Percent
1	Family-years (end-of-experiment point of view)	9,388	
2	and not in mixed-plans or HMO (after exclusion 1)	5,279	56.23% of row 1
3	and not first year in Dayton (after exclusions 1-2)	4,891	92.65% of row 2
4	and full year participation (after exclusions 1-3)	4,790	90.74% of row 2
5	and plan change (after exclusions 1-4)	4,767	90.30% of row 2
6	and complete MDE data (after exclusions 1-5)	4,763	90.23% of row 2
7	Family-years in analysis sample	4,763	

end-of-year prices are increasing with the coinsurance rate of the plan. The reported average realized end-of-year price per dollar of health care consumption is the coinsurance rate times the fraction of family-years who do not hit the TAT by the end of the coverage year. It varies between 0 in the free-care plan and 0.61 in the 95 percent coinsurance rate plans.

These differences in plan generosity translate into differences in average annual health care utilization. An average family in the free-care plan consumes $1,851 in health care services during a contract year. At the other extreme, an average family in the 95 percent coinsurance rate plan consumes $1,160 in health care services during a contract year. This implies that average health care utilization in the most generous plan is about 60 percent higher than that in the least generous plan. Table 2.2 also shows a steady increase of the percentage of family-years with zero annual health care utilization as the coinsurance rate increases. On average, the zero annual utilization rate is almost 3 times higher in the 95 percent coinsurance rate plans versus the free-care plan.

2.3 Evidence of Response to the Shadow Price of Care

Under standard nonlinear health insurance plans, an additional benefit of health care utilization today is lower future expected prices within the coverage period (typically one year). This section examines whether families' health care utilization decisions within the year respond to these dynamic pricing incentives. To do so, I derive a set of four testable implications for families who face a nonlinear pricing scheme coupled with uncertainty regarding future health care demand. The implications derived have only one key unobserved mechanism at play: the change in the shadow price of care within the year. Specifically, the higher the cumulative consumption and the more weeks left in the coverage period, the stronger are these incentives, i.e., the lower the shadow price of consumption. However, this is only true while families

Table 2.2: Plan characteristics and descriptive statistics of annual health care utilization

Coinsurance rate	0 percent	25 percent	50 percent	95 percent
Number of family-years	2,393	832	499	1,248
Plan features				
Premium ($)	0.00	0.00	0.00	0.00
Deductible ($)	0.00	0.00	0.00	0.00
Contract length (in years)	1.00	1.00	1.00	1.00
Coinsurance rate below TAT	0.00	0.25	0.50	0.95
Mean Total Annual Threshold ($)	0.00	2557.45	1560.65	744.54
Family total annual consumption				
Percentage with zero claims	4.47	6.13	8.22	12.74
Mean annual consumption ($)	1851.01	1284.92	1303.34	1159.95
Median annual consumption ($)	1022.35	598.37	436.57	329.305
Mean realized end-of-year OOP price	0.00	0.21	0.40	0.61
Mean outpatient share	0.34	0.37	0.40	0.35
Mean inpatient share	0.15	0.13	0.12	0.13
Mean dental share	0.30	0.27	0.235	0.25
Mean drug and supply share	0.14	0.15	0.15	0.13
Mean mental share	0.02	0.02	0.01	0.01
Family total annual consumption above TAT				
Proportion of family-years over TAT	1.00	0.1683	0.2084	0.3566
Mean share of TAT used	1.00	0.9559	1.8100	4.0620
Median share of TAT used	1.00	0.2468	0.2851	0.4917
Family-years over TAT | any inpatient	1.00	0.5150	0.6484	0.9040
Mean consumption above TAT ($)	1851.01	2428.09	3260.28	2219.70
Median consumption above TAT ($)	1022.35	1120.715	1130.375	1246.49

Notes: All expenditures are in dollars and cents for the year of service, unadjusted for inflation.

are below the cap. After they hit the cap they enjoy free care, and these dynamic incentives disappear.

In order to test these implications, I estimate linear regressions of the following form, where the dependent variable, y_{jtq}, is a measure of family j's health care utilization in contract week

t of experimental year q:

$$y_{jtq} = NonLastYear_{jq} \sum_{s=\substack{\text{below cap,}\\ \text{above cap}}} \left[\beta_0^s + \beta_1^s (T-t+1) + \beta_2^s \frac{Cum_{jtq}}{TAT_{jq}} + \beta_3^s (T-t+1) \frac{Cum_{jtq}}{TAT_{jq}}\right] + LastYear_{jq}\, \alpha^{\text{above cap}} + Family_j + \boldsymbol{\gamma}\, \mathbf{x}_{jtq} + \epsilon_{jtq}. \tag{2.1}$$

The variable $(T - t + 1)$ is the number of weeks left in the coverage period and the variable Cum_{jtq} is family j's cumulative health care utilization up to the beginning of week t of experimental year q. The variable $LastYear_{jq}$ is an indicator variable that equals 1 if q is the last year of participation in the experiment for family j and 0 otherwise (the opposite is true for $NonLastYear_{jq}$). As defined in the previous section, the variable TAT_{jq} stands for "Total Annual Threshold" and captures the family- and year-specific level of cumulative health care utilization above which the family enjoys free care for the remainder of the year. I also include family fixed effects, $Family_j$, to remove persistent heterogeneity across families, and dummy variables for calendar month, $\mathbf{x}_{jtq}$. By leveraging the experimental design, I can separate seasonality in health care demand from the dynamics of my model, since families have staggered enrollment dates.[22]

The key coefficients of interest are β_1^s, β_2^s, and β_3^s, which capture the response of weekly health care demand to the variation of the shadow price of care. Using equation (2.1), I derive four testable implications to evaluate whether families are sensitive to the dynamic incentives generated via the nonlinearities of health insurance plans.[23] The first two implications examine the behavior when families are below the cap on OOP spending, where the spot price is fixed but the shadow price varies. Focusing on the behavior after families exceed the cap, the last two implications address potential threats to identification of the response to the shadow price

[22]This is a unique feature since standard health insurance coverage begins and ends on the same date for almost all individuals (unless it is terminated due to job separation or death).

[23]The implications are tailored to the specific cost-sharing features and nature of the RAND HIE, in that they assume zero-dollar deductibles and exclude the last experimental year to avoid the end-of-experiment effect. They can easily be adapted to more general nonlinear contracts and insurance settings.

captured by the first two implications.

$$\frac{\partial \mathbb{E}\left[y_{jtq} \,\middle|\, Cum_{jtq} < TAT_{jq},\, NonLastYear_{jq} = 1\right]}{\partial (T - t + 1)} = \beta_1^{\text{below cap}} + \beta_3^{\text{below cap}} \frac{Cum_{jtq}}{TAT_{jq}} > 0, \tag{2.2a}$$

$$\frac{\partial \mathbb{E}\left[y_{jtq} \,\middle|\, Cum_{jtq} < TAT_{jq},\, NonLastYear_{jq} = 1\right]}{\partial (Cum_{jtq}/TAT_{jq})} = \beta_2^{\text{below cap}} + \beta_3^{\text{below cap}} (T - t + 1) > 0, \tag{2.2b}$$

$$\frac{\partial \mathbb{E}\left[y_{jtq} \,\middle|\, Cum_{jtq} \geq TAT_{jq},\, NonLastYear_{jq} = 1\right]}{\partial (T - t + 1)} = \beta_1^{\text{above cap}} + \beta_3^{\text{above cap}} \frac{Cum_{jtq}}{TAT_{jq}} = 0, \tag{2.2c}$$

$$\frac{\partial \mathbb{E}\left[y_{jtq} \,\middle|\, Cum_{jtq} \geq TAT_{jq},\, NonLastYear_{jq} = 1\right]}{\partial (Cum_{jtq}/TAT_{jq})} = \beta_2^{\text{above cap}} + \beta_3^{\text{above cap}} (T - t + 1) = 0. \tag{2.2d}$$

Implication (2.2a) states that a forward-looking family, whose accumulated health care utilization is held fixed at some level below the cap, should increase its utilization as the number of weeks left in the contract increases. This is because the family has more remaining opportunities to consume within the current contract, and, therefore, a higher probability of hitting the cap on OOP spending and enjoying free care for the remainder of the contract, all else equal. This situation drives the shadow price of care down and, therefore, encourages current utilization. An empirical test for Implication (2.2a) amounts to a test on the sign of the coefficients $\beta_1^{\text{below cap}}$ and $\beta_3^{\text{below cap}}$. This is because the ratio Cum_{jtq}/TAT_{jq} is always between 0 and 1. Therefore, a sufficient condition for Implication (2.2a) to hold is that $\beta_1^{\text{below cap}}$ and $\beta_3^{\text{below cap}}$ be jointly positive.

Implication (2.2b) states that, as the share of the cap consumed moves closer to 1, current health care utilization should increase holding the contract week fixed. The rate at which it increases depends on the number of weeks left in the contract. This response is driven by a decrease in the shadow price of care by taking into account the benefits of moving closer to the cap and potentially enjoying free care for the remainder of the contract. An empirical test for Implication (2.2b) accords naturally to a test on the sign of the coefficients $\beta_2^{\text{below cap}}$ and $\beta_3^{\text{below cap}}$. Notice that the variable $(T - t + 1)$ varies between 1 and 52. Therefore, a sufficient condition for Implication (2.2b) to hold is that $\beta_2^{\text{below cap}}$ and $\beta_3^{\text{below cap}}$ be jointly positive.

Up to this point, the key identifying assumption that allows me to interpret the estimates of Implication (2.2a) and (2.2b) as evidence of dynamic response to the shadow price of care is that there are no confounding effects on health care demand as the family approaches the end of the coverage horizon and the cap on OOP spending, conditional on being below the cap. In other words, any differential patterns of weekly health care demand that I observe across contracts weeks and proportion of the cap consumed are caused by differences in the shadow

price. However, this identifying assumption might not be correct if health care shocks are correlated across time (even after controlling for persistent heterogeneity at the family level) or if families increase health care utilization toward the end of the experiment in anticipation of being enrolled in a less generous plan after the experiment ends. The first scenario will bias my estimate of Implication (2.2b) away from 0, while the second scenario will bias my estimate of Implication (2.2a) toward 0. To investigate the validity of the identifying assumption, next I discuss the last two implications using families' health care utilization behavior once they exceed the cap on OOP spending.

Conditional on being above the cap, having more remaining opportunities to consume within the contract year should not impact current behavior. In other words, there are no further dynamics coming from the nonlinearities of the contract once above the cap, so weekly utilization should remain constant. An empirical test for Implication (2.2c) amounts to a joint test of the coefficients $\beta_1^{\text{above cap}} = 0$ and $\beta_3^{\text{above cap}} = 0$. This could fail in the presence of an *end-of-experiment* effect, for example, which I document in Appendix A.2, and constitutes the reason why I condition on non-last experimental years.[24] Implication (2.2c) could also fail if seasonality in health care demand cannot be separated from the dynamics via the nonlinear pricing (e.g., seasonal flu). To overcome this, I exploit the experimental design and use the variation in families' enrollment month to isolate seasonal demand.

After hitting the cap, families enjoy free care for the remainder of the contract year. Since current utilization does not affect within-the-year future prices, an increase in the share of the cap consumed should not impact current behavior. An empirical test for Implication (2.2d) amounts to a joint test of the coefficients $\beta_2^{\text{above cap}} = 0$ and $\beta_3^{\text{above cap}} = 0$. This could fail in the presence of correlated health shocks across time, even after removing persistent heterogeneity.[25] In order to capture this potential week-to-week correlation, I include family fixed effects in equation (2.1). The correlation I fail to capture with family fixed effects will show up in Implication (2.2d), and this is why this implication is central to my identification strategy. Since there is no shadow price variation left to exploit after exceeding the cap, any effect captured by $\beta_2^{\text{above cap}}$ points to week-to-week correlation in health shocks.

Table 2.3 displays the results of equation (2.1) using two measures of health care demand: an indicator for whether the family had any claim over the week and the level of health care

[24] Families participating in the RAND HIE knew that the experiment would end either after 3 or 5 years (randomly assigned before enrollment). This might induce an increase in health care utilization toward the end of the experiment if families anticipate being enrolled in less generous coverage plans after the experiment ends.

[25] Consider the situation of a family member who undergoes a hip replacement surgery at some point during the year. This situation most probably creates demand for further care (e.g., follow-up visits or further tests), which could generate positive serial correlation. This would contaminate the estimate of $\beta_2^{\text{below cap}}$ because I would attribute to a shadow price response a merely week-to-week correlation in health shocks.

utilization (in dollars) over the week. The first three rows show the estimates related with behavior below the cap on OOP spending, and the subsequent three rows show their counterpart once families exceed the cap. As predicted, families increased their weekly health care utilization level the further they were from the end of the contract year and the closer they were to the cap on OOP spending, conditional on being below the cap. This is consistent with families facing uncertainty about future health care demand, updating their probability of exceeding the cap over the course of the contract year, and having a positive discount factor. Once families exceed the cap, I find no statistically significant relationship between health care demand and weeks left or share of the cap consumed. I interpret this as supportive of the identifying assumption. Table 2.3 also confirms that the four testable implications hold as shown by the p-values from the joint F-tests.

To further delineate the dynamic response to the shadow price variation, I evaluate Implication (2.2a) at the mean level of the ratio Cum_{jtq}/TAT_{jq} in the middle of the contract year (i.e., at the beginning of week $t = 27$). I estimate that moving one month farther away from the end of the contract year is associated with a 1 percentage point increase in the probability of any weekly claim and a 2.8 percent increase in weekly family health care utilization, on average.[26] This estimate is in line with Aron-Dine, Einav, Finkelstein, and Cullen (2015) who find that enrollment a month earlier (and thus having one month more to reach the unadjusted deductible) is associated with a 1 percentage point increase in the probability of any claim and a 2.2 to 7.5 percent increase in health care utilization in the first three contract months.

Regarding Implication (2.2b), a 10 percentage point increase in the ratio Cum_{jtq}/TAT_{jq} is associated with a 1 percentage point increase in the probability of any weekly claim and a 5.9 percent increase in weekly family health care utilization, on average, when evaluated at the beginning of week $t = 27$.[27] To my knowledge, these are the first estimates of the relationship between within-year health care demand and proportion of the cap consumed using variation in the shadow price of care. These effects are exacerbated the further the family is from the end of the contract year or, in other words, when families have more opportunities remaining to consume. For example, when there are 11 months remaining, a 10 percentage point increase in the ratio Cum_{jtq}/TAT_{jq} is associated with a 2 percentage point increase in the probability of any weekly claim and a 10.9 percent increase in weekly health care utilization, on average.

Collectively, my results provide support for the hypothesis that families internalize the nonlinear nature of the incentive scheme and are responsive, in an statistically and economically meaningful way, to variation in the shadow price of care within the coverage period. While

[26] $\%\Delta y \approx 100 \times \frac{52}{12} \times \left[\beta_1^{\text{below cap}} + \beta_3^{\text{below cap}} \times \overline{\frac{Cum_{j(27)q}}{TAT_{jq}}}\right]$, with $\overline{\frac{Cum_{j(27)q}}{TAT_{jq}}} = 0.1778$.

[27] $\%\Delta y \approx 100 \times 0.10 \times [\beta_2^{\text{below cap}} + \beta_3^{\text{below cap}} \times (T - 27 + 1)]$, with $T = 52$.

Table 2.3: Weekly response to the variation in the shadow price of care

	(1) Share with any utilization	(2) Utilization in 2019 $ (in logs)
$\beta_1^{\text{below cap}}$: weeks left, non-last year	0.001***	0.003***
	(0.000)	(0.001)
$\beta_2^{\text{below cap}}$: cum to TAT ratio, non-last year	0.017	0.023
	(0.020)	(0.100)
$\beta_3^{\text{below cap}}$: interaction, non-last year	0.004***	0.021***
	(0.001)	(0.004)
$\beta_1^{\text{above cap}}$: weeks left, non-last year	0.000	-0.002
	(0.001)	(0.004)
$\beta_2^{\text{above cap}}$: cum to TAT ratio, non-last year	0.000	0.003
	(0.000)	(0.002)
$\beta_3^{\text{above cap}}$: interaction, non-last year	0.000	-0.000
	(0.000)	(0.000)
Cost Sharing Plans	Y	Y
Free Care Plan	N	N
Family fe	Y	Y
Clustered se	Y	Y
Families	1791	1791
Family-weeks	160784	160784
Adjusted R^2	0.23	0.22
p-value Implication 1: $\beta_1^{\text{below cap}} = 0$ and $\beta_3^{\text{below cap}} = 0$	0.000	0.000
p-value Implication 2: $\beta_2^{\text{below cap}} = 0$ and $\beta_3^{\text{below cap}} = 0$	0.000	0.000
p-value Implication 3: $\beta_1^{\text{above cap}} = 0$ and $\beta_3^{\text{above cap}} = 0$	0.898	0.675
p-value Implication 4: $\beta_2^{\text{above cap}} = 0$ and $\beta_3^{\text{above cap}} = 0$	0.638	0.279

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The table reports selected least-squares coefficients estimates from equation (2.1). Log variables are defined as log(var + 1) to accommodate zero values. I inflate health care utilization to 2019 prices using the monthly CPI-U. Standard errors clustered at the family level are in parentheses below the coefficients.

these regression models are useful for showing associations between variables, they are less useful for predicting how behavior may change in response to exogenous changes in policy. Estimation of the structural parameters of the explicit optimization problem provides for a better understanding of factors affecting health care demand and for the evaluation of alternative health insurance contracts. Informed by these findings, in the next section I develop a dynamic

model of weekly health care utilization decisions at the family level.

2.4 Model

My model is built around the problem of a forward-looking family who is enrolled in a general nonlinear health insurance plan for a given contract length. The nonlinearity of the plan arises from deductibles, coinsurance rates, and maximum out-of-pocket expenditures. In order to study the family's problem, I develop a single-agent, finite-horizon, dynamic, stochastic model of health care utilization at the family level combining elements of the annual model of health care demand from Einav, Finkelstein, Ryan, Schrimpf, and Cullen (2013) and the within-year model of internet demand from Nevo, Turner, and Williams (2016). An important feature of my model is that it explicitly incorporates the possibility of zero health care utilization as the optimal choice for a given period. Moreover, the generosity of insurance coverage can potentially affect the decision of whether or not to consume any health care.[28]

A period in my model is a contract week. After observing its realized health state, an expected-utility-maximizing family makes an optimal health care utilization decision every period. Since families are forward-looking, they form expectations on future health care utilization and internalize the dynamic pricing effect induced by the nonlinearities of the plan. This way, the model incorporates the fact that utilization decisions are made throughout the coverage period, before the uncertainty about subsequent health states is fully resolved.

2.4.1 Preliminaries

Families in my model are heterogeneous along several dimensions, which are unobserved to the econometrician and potentially correlated. For clarity of exposition, I omit the family subscript for now, and then in Section 2.5, I describe how families vary.

At the time of each weekly utilization choice, a family is characterized by its current health state realization ν, the beliefs about its subsequent health realizations $F_\nu(.)$, and its price sensitivity ω. The random variable ν captures the uncertain aspect of demand for health care, with higher ν representing sicker family members who demand greater health care utilization. The parameter ω determines how responsive health care utilization decisions are to insurance coverage. In other words, ω affects the family's price elasticity of demand for health care. Families

[28] The proportion of zeros is not a prominent feature in annual models of health care demand, so the literature has traditionally avoided corner solutions or defined a plan-invariant proportion of zeros.

with higher ω increase their utilization more sharply in response to more generous insurance coverage.

2.4.2 Utility Function

From the family's point of view, insurance coverage, denoted by k, is taken as given, and its health care utilization decision maximizes a trade-off between health and money. Following Einav, Finkelstein, Ryan, Schrimpf, and Cullen (2013), the family's per-period utility is separable in health and money and can be written as follows:

$$u(c_t; \nu_t, \omega, k) = \underbrace{\left[(c_t - \nu_t) - \frac{1}{2\,\omega}(c_t - \nu_t)^2\right]}_{b(c_t - \nu_t; \omega)} + \underbrace{\left[y_t - premium_{tk} - OOP(c_t, C_{t-1}; k)\right]}_{x(c_t)}, \tag{2.3}$$

where $c_t \geq 0$ represents the dollar consumption of covered health care goods and services for contract week t, including both the portion paid out-of-pocket by the family (if any) and the part paid by the insurance company; ν_t is the monetized health realization; and C_{t-1} represents accumulated health care utilization entering week t. I explicitly write the per-period residual income, $x(c_t)$, as the initial period-income y_t minus the per-period premium associated with coverage k and the out-of-pocket expenditure $OOP(c_t, C_{t-1}; k)$ associated with utilization c_t under coverage k.[29] Naturally, $x(c_t)$ is (weakly) decreasing in c_t at a rate that depends on coverage k.[30]

The first term $b(c_t - \nu_t; \omega)$ is quadratic in its first argument, with ω affecting its curvature. It is increasing for low levels of utilization, when treatment improves health, and is decreasing eventually, when there is only marginal health benefit from treatment and time costs dominate. Thus, the marginal benefit from incremental utilization is decreasing. Using this formulation, the underlying health realization ν_t plays the role of shifting the level of optimal health care utilization, $c_t^\star$. Since ω is constrained to be strictly positive, period utility is increasing in ω.

To facilitate intuition, I consider here optimal utilization under a linear coverage contract where the OOP price remains constant throughout the year irrespective of past cumulative utilization. Thus, $OOP(c, .; k) = coins_k \times c$, where $coins_k$ represents the constant coinsurance

[29] I denote the remaining consumption before the TAT is reached as $\overline{C_t} = \overline{C_t}(C_{t-1}; k) \equiv \max\{\text{TAT}_k - C_{t-1}, 0\}$. Then, under zero-deductible contracts, I can define $OOP(c_t, C_{t-1}; k) \equiv coins_k \times \min\{c_t, \overline{C_t}\}$.

[30] This structure assumes that a family consumes all per-period income by the end of each contract week, as saving decisions are not observed in the data. This is a standard assumption in this literature.

rate of coverage k, $coins_k \in [0, 1]$. Per-period optimal health care utilization is given by

$$c^\star(\nu, \omega; k) = \max[0, \nu + \omega \times (1 - coins_k)]. \tag{2.4}$$

Abstracting from the potential truncation of utilization at zero, the family optimally chooses $c^\star = \nu$ under no insurance, i.e., when $coins_k = 1$, and $c^\star = \nu + \omega$ under full insurance, i.e., when $coins_k = 0$. Thus, ω can be thought of as the incremental utilization attributed to the change in coverage from no insurance to full insurance or, in other words, the full scope of moral hazard (per period).

As can be seen from equation (2.3), families enrolled in a general nonlinear health insurance plan do not always pay the total price of health care because of the plan's cost-sharing arrangement. Rather, a family pays a dollar amount out-of-pocket that is determined by the total price of health care, insurance plan characteristics, and accumulated health care utilization during the coverage period. As a consequence, the family faces a nonlinear budget set. The out-of-pocket expenditure function, $OOP(.)$, contains these nonlinearities.

Consider the case of a family enrolled in a plan with no deductible, a 25 percent coinsurance rate, and maximum out-of-pocket expenditure of \$750. Entering a given week with \$0 accumulated health care consumption, this family is charged \$1,000 for a medical visit. In this case, the family pays \$250 out of pocket (i.e., $\min[0.25 \times 1,000, 750]$). However, if the same family were to have accumulated \$2,500 in health care utilization prior to the visit, including both the portion paid out-of-pocket and the part paid by the insurance company, then it would pay only \$125, which is the minimum between \$250 and what is left to hit the family's maximum out-of-pocket expenditure of \$750.[31]

The timing of the model is as follows. At the beginning of contract week t, families learn their realization of the period-t health state, ν_t. Taking into account the plan characteristics, the accumulated health care utilization, and the expected future health risk, families choose the optimal level of health care utilization for period t. By the end of contract week t, families update their accumulated health care utilization level, which under a general nonlinear contract determines the price of health care for the subsequent contract week.

Utility from covered health care services is assumed to be additively separable over all weeks in the coverage period. For any given health insurance plan k, denote the number of weeks in the coverage period by T_k. Conditional on being enrolled in insurance plan k, the

[31] A family enrolled in a zero-deductible plan, with a 25 percent coinsurance rate, and maximum out-of-pocket expenditure of \$750 has an associated TAT of \$750/0.25 = \$3000. Following the notation of equation (2.3), $OOP(1000, 2500; k) = 0.25 \times \min[1000, (3000 - 2500)] = \$125$.

family's problem is as follows:

$$\max_{\{c_1,\ldots,c_{T_k}\}\in\mathbb{R}_+^{T_k}} \quad \sum_{t=1}^{T_k} \delta^{t-1}\mathbb{E}[u(c_t;\nu_t,\omega,k)], \quad \text{s.t.} \begin{cases} OOP(C_{T_k},0;k) + Y_{T_k} + premium_k \leq I\,, \\ C_{T_k} = \sum_{t=1}^{T_k} c_t, \quad Y_{T_k} = \sum_{t=1}^{T_k} y_t\,, \end{cases} \tag{2.5}$$

where δ represents the weekly discount rate. From a period-t point of view, the expectation is taken with respect to the uncertainty involving the future health realizations ν_m, $m = \{t+1,\ldots,T_k\}$. I assume that wealth, I, is large enough so that it does not constrain covered health care utilization decisions.[32]

2.4.3 The Dynamic Optimization Problem

The family's objective is to maximize the expected discounted future utility by selecting the optimal sequence of health care utilization, c_t, for $t = 1,\ldots,T_k$. In this subsection, I describe the family's dynamic optimization problem that captures the health care utilization decisions made repeatedly over the course of a coverage period, taking into account the uncertainty about subsequent health states.

In the last contract week of the coverage period, T_k, the model becomes static: cumulative health care utilization resets to zero at the beginning of the following coverage period despite the period-T_k decision. Denote the period-T_k optimal level of covered health care utilization by the function $c^\star_{T_k} = c^\star_{T_k}(C_{T_k-1},\nu_{T_k};k)$. The family's utility in the terminal period is then given by

$$V_{T_k}(C_{T_k-1},\nu_{T_k};k) = (c^\star_{T_k} - \nu_{T_k}) - \frac{1}{2\,\omega}\,(c^\star_{T_k} - \nu_{T_k})^2 + x(c^\star_{T_k})\,. \tag{2.6}$$

For any other week $t < T_k$, covered health care utilization counts toward the family's TAT and affects the next period's state, so the optimal policy function for a family incorporates this. I therefore solve for the optimal health care utilization decision recursively. Then the family's optimal decision in period t satisfies

$$c^\star_t(C_{t-1},\nu_t;k) = \max\left[0, \nu_t + \omega\left(1 - \frac{\partial OOP(c_t,C_{t-1};k)}{\partial c_t} + \delta\frac{\partial\mathbb{E}[V_{t+1}(C_{t-1}+c_t,\nu_{t+1};k)]}{\partial c_t}\right)\right], \tag{2.7}$$

where the term $\partial OOP(.)/\partial c_t$ represents the spot price of care and the term $\partial\mathbb{E}[V_{t+1}(.)]/\partial c_t$ captures the reduction in future expected prices via the nonlinearities of the contract.

[32] This is a reasonable assumption in the context of my data since the RAND HIE features low caps relative to income.

In each decision period t, the state is defined by three components. First, the contract week t which determines the number of weeks left until the end of the coverage period, $T_k - t + 1$. Second, the accumulated health care utilization up until period t, C_{t-1}. And third, the stochastic health state ν_t which is known to the family at the beginning of period t. So the vector (t, C_{t-1}, ν_t) provides a complete description of the state at time t. For brevity, I describe the state vector as (C_{t-1}, ν_t) and index the policy and value functions by t.

The value function for each ordered pair (C_{t-1}, ν_t) and for any $t < T_k$ is given by

$$V_t(C_{t-1}, \nu_t; k) = \max_{c_t} \Big[u(c_t; \nu_t, \omega, k) + \delta \mathbb{E}\big[V_{t+1}(C_t, \nu_{t+1}; k)\big] \Big], \tag{2.8}$$

where $c_t \geq 0$ and $C_t = C_{t-1} + c_t$.

To provide a clear understanding of the dynamic pricing effect, abstract for a moment from the discontinuous nature of the nonlinear price structure and the potential truncation of utilization at zero. Then, the solution to equation (2.8) would be characterized by the following first-order condition:

$$\frac{\partial u}{\partial c_t} + \frac{\partial u}{\partial x_t} \frac{\partial x_t}{\partial c_t} + \delta \mathbb{E}\left[\frac{\partial V_{t+1}}{\partial C_t} \right] = 0 \,. \tag{2.9}$$

The first term reflects the consumption value of health care. The second term reflects the direct monetary cost of that consumption, expressed in utility terms. Finally, the third term reflects the effect of current health care utilization on future expected prices. It is this last effect that is of central interest in this paper.

2.4.4 The Shadow Price of Health Care

The shadow price of health care is a combination of the spot price and the option value associated with lower future expected prices. In a multi-period model with uncertain future health needs and a nonlinear price schedule, any health care expenditure below the TAT reduces the remaining distance to the TAT and, hence, the future expected prices. I define the *shadow price* of covered health care as

$$\widetilde{sp}_t(c_t, C_{t-1}; k) = \begin{cases} \dfrac{\partial OOP(c_t, C_{t-1}; k)}{\partial c_t} - \delta \dfrac{\partial \mathbb{E}[V_{t+1}(C_{t-1} + c_t, \nu_{t+1}; k)]}{\partial c_t} & , \text{ if } \quad C_{t-1} + c_t < TAT_k \\ 0 & , \text{ if } \quad C_{t-1} + c_t \geq TAT_k \end{cases}, \tag{2.10}$$

where the first part of equation (2.10) represents the shadow price for families who have not reached their caps on OOP spending yet, while the second part shows the shadow price

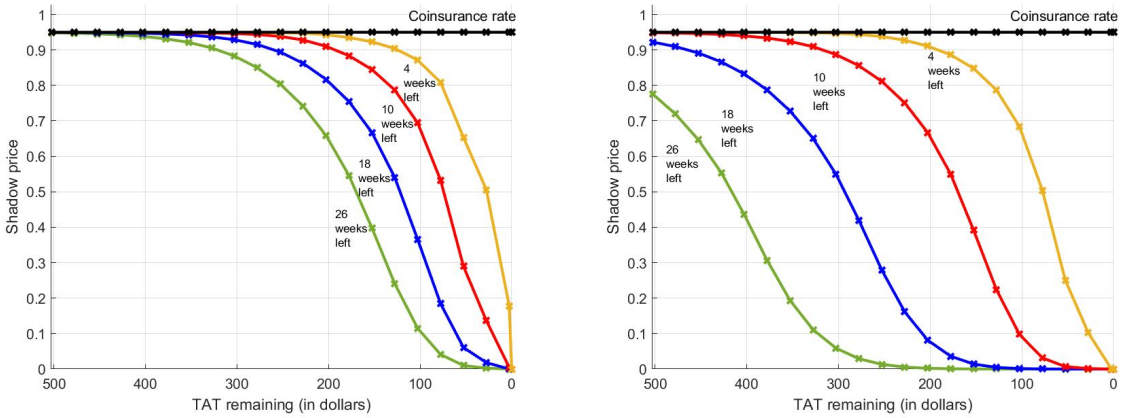
once they hit the cap. The shadow price of care is equal to the marginal out-of-pocket price, $\partial OOP(.)/\partial c_t$, minus the marginal value of reducing the remaining distance to hit the cap. This latter value is the rate a family would pay (ex ante) to exchange the current insurance policy for one with the TAT reduced by one dollar.

The presence of the term $\partial \mathbb{E}[V_{t+1}(.)]/\partial c_t$ is the crucial distinction between my model and annual models or multi-period, static models of health care demand. In annual models, the shadow price of care always coincides with the end-of-year price. This is because families make a one-shot decision regarding their total annual health care utilization, which place them either below the deductible, between the deductible and the cap, or above the cap with certainty. In other words, annual models remove the uncertainty about future health care needs, so that families have perfect foresight about their end-of-year price and adjust their annual health care utilization decision accordingly. Multi-period static models assume that families are myopic and respond only to the out-of-pocket price of the period they are taking the decision. So in these models, the shadow price always coincides with the spot price of health care.

Figure 2.2 provides a graphical illustration of the properties of the shadow price for a family with a zero-deductible plan, a 95 percent coinsurance rate, and a $1,000 cap on OOP spending. In order to compute the option value component of the shadow price I need to specify values for the distribution of health shocks F_ν and the price sensitivity ω, although the patterns displayed in the figure hold generally. In panel 2.2(a) I use values corresponding to a low mean of F_ν and in panel 2.2(b) a high mean. There are three main properties to highlight. First, the shadow price ranges from 0 (once the cap is hit) to the coinsurance rate of 0.95. Second, as cumulative expenditures increase and the TAT remaining falls, the shadow price also falls. Third, the rate at which it falls is increasing in the amount of time left. These last two properties capture the mechanisms I document using data from the RAND Health Insurance Experiment (see Implications (2.2a) and (2.2b) in Section 2.3).

The shadow price of care also depends on expected future health care needs. Intuitively, the marginal value of reducing the remaining distance to hit the cap is lower for relatively healthy people, whose probability of becoming sick in the future is low, compared to people with poor health, *ceteris paribus*. Figure 2.2(b) shows the shadow price for a family sicker than the one considered in Figure 2.2(a), in that it has a higher mean of the health shocks distribution. As can be seen, the shadow price curves shift inwards, implying that the shadow price falls as the mean health risk increases. It can also be shown that if the variance of the shocks rises, given a constant mean, the shadow price curves become less steep (see Appendix A.3).

Figure 2.2: Model properties of the shadow price of care



(a) Shadow price, low mean of F_ν

(b) Shadow price, high mean of F_ν

2.5 Econometric Specification

I estimate the model developed in Section 2.4 by extending the approach proposed by Ackerberg (2009), Bajari, Fox, and Ryan (2007), Fox, Kim, Ryan, and Bajari (2011), and Fox, Kim, and Yang (2016); and recently applied by Nevo, Turner, and Williams (2016) in the context of demand for residential broadband and Blundell, Gowrisankaran, and Langer (2020) in firms' investment decisions in pollution abatement technologies. This framework allows me to incorporate flexibly-correlated unobserved heterogeneity in several dimensions related to family health risk, preferences for visiting a doctor, and price sensitivity, without requiring parametric assumptions. The structural estimation of the model proceeds by combining a method-of-moments approach with a simple nonparametric estimator for the distribution of the correlated random coefficients. This section presents the estimation approach and discusses identification.

2.5.1 Parameterization

Families in my model are defined by their beliefs about their subsequent health status $F_\nu(.)$, their price sensitivity parameter ω, and their previous year (PY) income. I allow all these objects to flexible vary across families, but assume they remain constant within a contract year. Yet the family type can change across experimental years to capture cross-year differences in family composition that may affect health care demand.

The health state ν_{th} is a time-varying and type-specific health shock, which represents the

period-t shock to the family's health capital stock.[33] Health realizations ν_{th} are assumed to be independently and identically distributed and drawn from a (shifted) log-normal distribution with support (κ_h, ∞). The assumption of no cross-week correlation in health shocks after conditioning on family type is in line with my estimates of implication (2.2d) in Section 2.3 and the findings in previous literature.[34]

Before the uncertainty is resolved, families believe that

$$\log(\nu_{th} - \kappa_h) \sim N(\mu_h, \sigma_h^2)\,, \tag{2.11}$$

and these beliefs are correct. Assuming a log-normal distribution for ν is natural, as the distribution of weekly health care utilization is highly skewed. The additional parameter κ_h is used to capture the significant fraction of families who have zero health care utilization within a week. When κ_h is negative, the support of the implied distribution of ν_{th} is expanded, allowing for ν_{th} to obtain negative values, which may lead to zero health care demand. Therefore, expected health care needs for a week are given by

$$\bar{\nu}(\mu, \sigma, \kappa) = \exp(\mu + 0.5\,\sigma^2) + \kappa\,. \tag{2.12}$$

Finally, I include PY income as a component of the family type to capture the variability of the cap on out-of-pocket expenditures within each experimental plan.[35]

2.5.2 Estimation

I estimate the joint distribution of unobserved heterogeneity using a method-of-moments approach similar to the two-step algorithms proposed by Ackerberg (2009), Bajari, Fox, and Ryan (2007), and Fox, Kim, Ryan, and Bajari (2011); and first applied by Nevo, Turner, and Williams (2016). This estimator is flexible, easy to program, and computationally advantageous compared to alternative estimators for random coefficient models. For complex structural dynamic models, one does not need to nest a solution to the economic model during optimization. The estimator uses a finite and fixed grid of random coefficient vectors as mixture components

[33] ν_{th} captures the composite shock from illnesses at period t plus health capital depreciation from period $t-1$ to period t.

[34] See e.g., Einav, Finkelstein, and Schrimpf (2015) in the context of Medicare Part D, who find that conditional on allowing for unobserved heterogeneity across individuals in their permanent health state, the remaining week-to-week correlation is not very important.

[35] Income is the only dimension of family heterogeneity in the model that is observable to the econometrician, although only partially. The income distribution is censored from above, because I can only recover income from those families with MDEs strictly smaller than $1,000.

to construct the distribution from the estimated probability weight of every component. The methodology exploits a re-parametrization of the underlying model so that the new parameters of interest (the weights on each type) enter linearly. Because of this linearity, the model can be estimated using inequality constrained least squares (ICLS). The ICLS minimization problem is convex, so a standard least squares algorithm will find a global optimum. By reducing the computational burden, the methodology allows me to relax several strong assumptions frequently imposed on the joint distribution of random coefficients. I do not need to assume that the random coefficients are mutually independent or that they are symmetrically distributed. The statistical and shape properties of the distributions are learned directly from the data once the parameters are estimated.

These advantages of the Fox, Kim, Ryan, and Bajari (2011) estimator are in contrast to previous approaches in the literature, which are highly nonlinear and computationally expensive. Researchers have tended to specify a parametric distribution and estimate its parameters. Estimation usually proceeds by simulation: maximum likelihood or the method of moments. These methods are computational demanding, specially for high-dimensional vectors of random coefficients (Bajari, Fox, and Ryan, 2007). Moreover, the specified distributions usually feature undesired properties.[36] Nonparametric methods offer the possibility of not being as constrained by distributional assumptions. The most common frequentist, mixtures estimator is nonparametric maximum likelihood (Heckman and Singer, 1984). Often the expectation-maximization (EM) algorithm is used for computation, which is sensitive to its starting values and is not guaranteed to converge to a global optimum. Moreover, the number of support points allowed is generally small, often only two or three, and can take the wrong sign if estimation is not constrained. Hierarchical Bayesian estimation is an alternative (Rossi, McCulloch, and Allenby, 1996). For example, Einav, Finkelstein, Ryan, Schrimpf, and Cullen (2013) employ a Bayesian hierarchical model to approximate the random coefficients' distribution. The estimator uses a Markov Chain Monte Carlo Gibbs sampling, which requires training and monitoring by the user. Moreover, the procedure usually involves evaluating the objective function many times, which is computational demanding specially in complex dynamic models.

I overcome these limitations by using the methodology of Fox, Kim, Ryan, and Bajari (2011), which consists of two steps: a computational step and an estimation step. For the computational step, I fix a large but finite grid of H types in the five-dimensional space, where a family type is characterized by the vector $\boldsymbol{\beta}_h = (\mu_h, \sigma_h, \kappa_h, \omega_h, PYincome_h)$. Then, for each

[36]The normal distribution is probably the most widely used; however, its support on both sides of zero makes it problematic for coefficients that are necessarily signed. Lognormal distributions are usually used to avoid wrong signs. Yet they have relatively thick tails extending without bound, which implies that a share of the population has implausibly large values for the relevant coefficients (Train, 2008).

plan k and family type h, I solve the finite-horizon dynamic programming problem described in Section 2.4 recursively, starting from the last period T_k, and solving backwards period-by-period until the first contract week, and collecting the sequence of decision rules in each t. This way I construct the optimal policy given initial condition $C_0 = 0$ and any realization of $\{\nu_t\}_{t=1}^{T_k}$. Because a family does not know the realization of the health demand shock ν_t prior to period t, I integrate over its support. The solution to the dynamic programming problem for each plan and family type can be characterized by the expected value functions, $\mathbb{E}[V_t(C_{t-1}; k, h)]$, and expected policy functions, $\mathbb{E}[c_t^\star(C_{t-1}; k, h)]$. The solution to the dynamic program implies a distribution for the number of weeks spent in particular states (t, C_{t-1}) over a coverage period.

In the second stage, I estimate the weight associated with each family type, θ_{kh}, to match the weighted average of the behavior predicted by the model to moments from the data using inequality constrained least squares. Each moment $G_j(\boldsymbol{\theta}_k)$ can be written as the difference between some moment in the data and the weighted average of the type moments predicted by the model:[37]

$$G_j(\boldsymbol{\theta}_k) = m_{kj}^{\text{data}} - m_{kj}^{\text{model}}(\boldsymbol{\theta}_k) = m_{kj}^{\text{data}} - \sum_{h=1}^{H} \theta_{kh} \times m_{kjh}^{\text{model}}(\boldsymbol{\beta}_h). \tag{2.13}$$

The key insight from equation (2.13) is that the new parameters of interest $\boldsymbol{\theta}_k$ enter linearly, irrespective of the highly nonlinear model used to compute the type-specific moments $m_{kjh}^{\text{model}}(\boldsymbol{\beta}_h)$. Formally, for each plan k, the methodology chooses weights $\widehat{\boldsymbol{\theta}}_k$ to satisfy

$$\widehat{\boldsymbol{\theta}}_{\boldsymbol{k}} = \text{argmin}_{\boldsymbol{\theta}_k} G'(\boldsymbol{\theta}_k) G(\boldsymbol{\theta}_k) \quad \text{subject to} \quad \begin{cases} \theta_{kh} \geq 0 \quad \forall h \\ \sum_{h=1}^{H} \theta_{kh} = 1 \\ \sum_{h=1}^{H} \theta_{kh} \times \mathbb{1}[\text{MDE}_{kh} \in \text{bin}_r] = \pi_{kr}^{\text{data}} \end{cases} \tag{2.14}$$

The first two sets of constraints in equation (2.14) restrict the weights to be non-negative and to sum up to 1 for each plan. The last set of constraints uses the plan-specific empirical distribution of OOP limits to partition the type distribution according to the type-specific PY income.[38] For each plan k, the number of unknown parameters is the number of types, $dim(\boldsymbol{\theta}_k) = H$. Then,

[37] Following Bajari, Fox, and Ryan (2007), the second term of equation (2.13) is a series estimator that approximates an unknown function $\widetilde{m}_{kj}^{model}$ with the approximation $\widetilde{m}_{kj}^{model} \approx \sum_{h=1}^{H} \theta_{kh} \times m_{kjh}^{model}(\boldsymbol{\beta}_h)$. The basis functions are not the flexible mathematical functions from traditional series estimators, but the predictions of a single-agent, finite-horizon, dynamic, stochastic model of health care demand for a family of type h enrolled in health insurance plan k. The unknown frequencies θ_{kh} are structural objects, not just the approximation weights from series estimation.

[38] For each plan, I partition the empirical distribution of OOP limits in 11 bins. The first ten bins correspond to the deciles of the distribution. The last bin collects all types with caps equal to \$1,000.

I construct the estimated cumulative distribution function for the random coefficients as

$$\widehat{F}(\boldsymbol{\beta}; k) = \sum_{h=1}^{H} \widehat{\boldsymbol{\theta}}_k \times \mathbb{1}[\boldsymbol{\beta}_h \leq \boldsymbol{\beta}], \tag{2.15}$$

where $\mathbb{1}[\boldsymbol{\beta}_h \leq \boldsymbol{\beta}] = 1$ when $\boldsymbol{\beta}_h \leq \boldsymbol{\beta}$. Thus, this method provides a structural estimator for the distribution of random parameters for each plan k. This estimator is consistent under standard regularity conditions.[39]

Following Nevo, Turner, and Williams (2016), I choose the following moments because they have a clean connection to weekly and cumulative utilization. For each plan k, I match three sets of moments. The first set of moments is related to the mass of families at a particular state (C_{t-1}, t) or, in other words, the fraction of observations at each state. These moments capture the distribution of cumulative utilization at the end of each contract week. For example, the end-of-year distribution of cumulative utilization, which reflects the distribution of annual utilization, is a subset of moments in this set. Formally, moments in this set are given by

$$m^{model}_{kjh,\text{set }1}(\boldsymbol{\beta}_h) = \sum_{h=1}^{H} \gamma_{kjh}(C_{t-1} = C_s), \tag{2.16}$$

where j indexes combinations of time t and thresholds s, and $\gamma_{kjh}(C_{t-1} = C_s)$ represents the probability that a family of type h enrolled in plan k reaches contract week t with C_s dollars in accumulated health care utilization within the coverage period.

For the second set of moments, I use the mean health care utilization at each state (C_{t-1}, t), which captures the weekly utilization level and how it varies with the cap remaining and the weeks left:

$$m^{model}_{kjh,\text{set }2}(\boldsymbol{\beta}_h) = \sum_{h=1}^{H} \gamma_{kjh}(C_{t-1} = C_s) \times \mathbb{E}[c^{\star}_{kht} | C_{t-1} = C_s], \tag{2.17}$$

where $\mathbb{E}[c^{\star}_{kht} | C_{t-1} = C_s]$ is the mean weekly utilization in contract week t for a family of type h enrolled in plan k, conditional on past accumulated utilization level $C_{t-1} = C_s$.

Finally, the third set of moments is the mean probability of zero utilization at each state (C_{t-1}, t). These moments are different from Nevo, Turner, and Williams (2016). Unlike internet usage and annual health care demand, zeros are a much more prominent feature in my weekly

[39] See Andrews (2002) who show that consistency is not affected by linear inequality constraints.

health care utilization data. Formally,

$$m^{model}_{kjh,\text{set }3}(\boldsymbol{\beta}_h) = \sum_{h=1}^{H} \gamma_{kjh}(C_{t-1} = C_s) \times \Pr[c^{\star}_{kht} = 0 | C_{t-1} = C_s], \tag{2.18}$$

where $\Pr[c^{\star}_{kht} = 0 | C_{t-1} = C_s]$ is the probability that a family of type h enrolled in plan k does not consume covered health care services in contract week t, conditional on past accumulated utilization level $C_{t-1} = C_s$. Note that in all three sets of moments, the average is taken across all types of families in the plan, not just those that arrive at the particular state (C_{t-1}, t) with positive probability. This keeps the moments linear in the parameters $\boldsymbol{\theta}_k$, which is particularly attractive from the perspective of computational ease. Appendix A.4 provides additional details regarding how I construct the data counterparts of these three sets of moments.

Similar to Nevo, Turner, and Williams (2016) and Blundell, Gowrisankaran, and Langer (2020), I use a nonparametric block-resampling procedure to obtain standard errors for my structural parameters estimates, $\boldsymbol{\theta}_k$. Specifically, I sample the original data by family-year with replacement, keeping all 52 weeks for each of the family-years drawn. For each of 1,000 bootstrap samples, I recalculate the three sets of moments and then re-estimate the weights separately for each plan. I calculate confidence intervals for subsequent statistics and counterfactual analyses by repeating the calculation using the 1,000 different estimates of the weights.[40]

2.5.3 Choice of Grid Points

As mentioned earlier in this section, the methodology treats the grid of random coefficients as known and fixed. Thus, it requires the ex-ante specification of parameter grid values. In order to choose the points for the discrete five-dimensional family-type space, I follow the method of good lattice points (hereafter, *glp*). This approach has been proposed in economics by Judd (1998) in the context of integration and simulation, but to the best of my knowledge has not been applied to the estimation of dynamic programming problems. The *glp* method generates a finite set of "quasi-random" points with the property of low *discrepancy*.[41] The discrepancy of a set is a measure of how dispersed a collection of points is. Essentially, it measures the deviations from uniformity of different sets of points and provides a formal way to rank them.[42]

[40] A step-by-step description of the bootstrap procedure is provided in Appendix A.4.4.

[41] Blundell, Gowrisankaran, and Langer (2020) choose their grid values by using co-prime Halton sequences, an alternative method to generate quasi-random numbers.

[42] Roughly speaking, the discrepancy of a collection of points in the interval $[0, 1]$ is low if the proportion of points in the set falling into an arbitrary subinterval $[a, b]$, $0 \leq a \leq b \leq 1$, is proportional to the length of that interval. For a more formal treatment of low-discrepancy methods, see Section 9.2 of Judd (1998).

A small discrepancy says that the collection of points evenly fills up the hypercube I^d, where d is the dimension of the grid. More details about the *glp* method can be found in Appendix A.5.

A more common approach for the choice of grid points is the one followed by Nevo, Turner, and Williams (2016), which I call the method of tensor product points (hereafter, *tpp*). This standard approach consists of choosing the support points in each dimension separately, and then building the grid with all the possible combinations of them. For example, Nevo, Turner, and Williams (2016) choose seven points of support for each of their five dimensions of unobserved heterogeneity and build a grid with $7^5 = 16,807$ types. The *tpp* approach generates a lot of overlap between the points. I find that the *tpp* approach needs at least 50 times more points than the *glp* approach to achieve the same fit. Results of this Monte Carlo exercise are presented in Appendix A.6.

In order to assess the discrepancy of the sets produced by these two methods, I apply a simple discrepancy test.[43] I generate 1,000 random hypercubes of dimension five, check their discrepancy, and report the maximum discrepancy as the desired statistic. It is relevant to emphasize that, the smaller the discrepancy, the more uniformly distributed the points are inside the hypercube, and the more accurate mass points can be captured. I calculate the discrepancy for 1,000 sets of 1,069 *glp* and 1,000 sets of 16,807 *tpp* coming from seven uniformly distributed points on [0,1] in each of the 5 dimensions. The maximum discrepancies are 0.0135 and 0.3996, respectively. Therefore, the *glp*'s measure is 30 times smaller than the *tpp*'s measure. This means that in the worst scenario, the *glp* method produces points that are 30 times more uniformly distributed than the ones generated by the *tpp* method. From a statistical standpoint, a collection of points with the smaller discrepancy captures the joint distribution of random coefficients more accurately.

2.5.4 Identification

Conditional on the model described in Section 2.4, the objective is to identify the joint distribution of the parameters governing the health risk distribution, $F_\nu(.)$, the price sensitivity, ω, and the PY income. Following Fox, Kim, Ryan, and Bajari (2011), I use a nonparametric finite mixture model by fixing a large but finite grid of five-dimensional points. This way, the support points of the multivariate distribution, $\{\boldsymbol{\beta}_h\}_{h=1}^H = \{(\mu_h, \sigma_h, \kappa_h, \omega_h, \text{PY income}_h)\}_{h=1}^H$, are treated as known, and the parameters to identify are the weights, $\{\theta_{kh}\}_{h=1}^H$, on the support points. Since equation (2.14) accords to a linear regression subject to inequality constraints, the weights are identified as long as the matrix of model moments has full rank. In other words, the weights

[43] I thank Ken Judd for suggesting this empirical test.

are identified as long as the behavior predicted by different types is not collinear over all the moments and all states used in estimation. Next I discuss how each parameter in the type vector $\boldsymbol{\beta}_h = (\mu_h, \sigma_h, \kappa_h, \omega_h, \text{PY income}_h)$ impacts the variation in predicted behavior across moments and states.

The intuition works similarly to Nevo, Turner, and Williams (2016), although I adapt and extend it to my context.[44] In Nevo, Turner, and Williams (2016), all dimensions of the space of types are unobserved by the econometrician. In my context, four out of the five dimensions are unobserved, while family's PY income is censored from above. As a consequence, my identification strategy differs according to the observability of the source of permanent heterogeneity. In what follows, I first discuss the identification of the distribution of each unobserved dimension and then explain how I can provide additional identification by exploiting the variation of PY income. The identification of unobserved dimensions relies on matching the moments related to the timing and the level of weekly health care consumption observed in the data with their counterpart moments predicted by the model. The identification of the income dimension comes through the constraints imposed on the weights.

Fixing σ_h and κ_h, a higher value of μ_h generates a higher value of the weekly health shock ν_h, which in turns induces a (weakly) higher average weekly health care consumption.[45] Here, the panel dimension of my data emerges as an important determinant for identification. By modeling weekly decisions, I can identify the persistence in health care consumption that comes through the time-invariant health risk distribution of the family.

Fixing μ_h and κ_h, a change in σ_h impacts the variance of weekly consumption and therefore the likelihood of reaching certain states. This is because the lower the variance, the lower the likelihood of reaching extreme states (i.e., cumulative consumption states far apart from what the mean consumption would dictate).

The parameter κ governs the shift of the log-normal distribution of weekly health shocks. When κ is negative, the weekly shocks can take negative values, which can lead to zero consumption. Hence, κ affects primarily the extensive margin of weekly health care consumption. In particular, the set of moments related to the probability of zero consumption in each state aids in the identification of the distribution of κ.

Identification of the price sensitivity parameter ω exploits the nonlinearity of the contracts induced by the presence of the cap on annual out-of-pocket expenditures. Within plan and fixing ω, changes in the shadow price of care generate variation in the consumption level that

[44] The logic behind the identification follows closely the formal argument in Kasahara and Shimotsu (2009).

[45] Since $\log(\nu_h - \kappa_h) \sim N(\mu_h, \sigma_h^2)$, the average health shock not only depends on μ_h but also σ_h as well as κ_h. For the exact formula, see equation (2.12).

aids in the identification of ω. Hence, how likely and early a family hits the cap provides a dynamic source of identification for ω. Table 2.2 in Section 2.2 showed that between 17 and 36 percent of family-years on plans with nonlinear pricing exceed their cap. This is important, as one source of variation needed to identify the distribution of ω relies on having enough families with a positive probability of exceeding the TAT during the contract year.

On top of the four unobserved dimensions of the type space, each type has one observed component: the family's PY income, which impacts behavior only through the cap on out-of-pocket expenditures. Hence, even though the distribution of income is censored from above in the data, the distribution of MDE is fully observed. I divide the possible MDE values in eleven groups, in an attempt to balance the trade-off between adding more sources of identification versus putting more pressure on the fit. The share of family-years in each MDE bin provides information on the type distribution. In the model, each type belongs to one and only one MDE bin. So family's PY income and plan characteristics split the type space into distinct groups. In other words, they put a weight on each group of types equal to the share of family-years who belong to each MDE bin.

2.6 Results

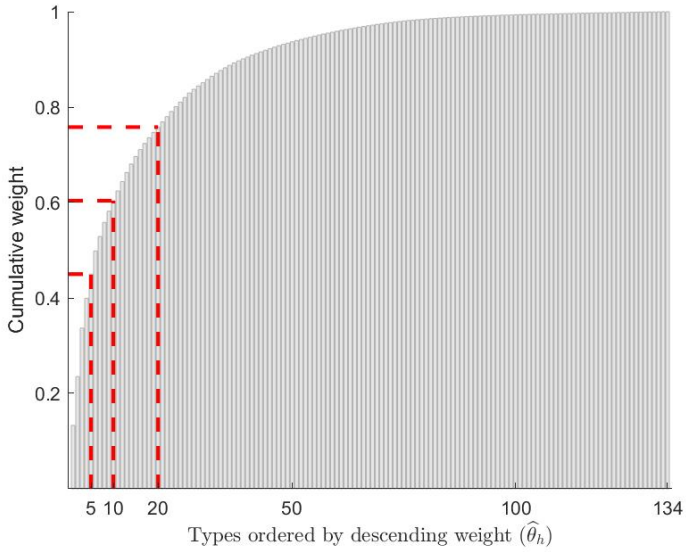
This section begins with a discussion of the estimated type distribution, implied quantities, and model fit. I then provide estimates of the impact that moral hazard has on health care consumption and compare these estimates to the literature.

2.6.1 Type Distribution

I estimate a weight greater than 0.01 percent (i.e., $\theta_h > 0.0001$) for 134 types out of 1,069 considered. The first feature I find is substantial heterogeneity in the distribution of weights. The most common type accounts for 13.3 percent of the total mass, the top 5 types account for 45 percent, the top 10 for 60.4 percent, and the top 20 for 75.8 percent. Figure 2.3 shows the cumulative distribution of weights ordered from the most to least common type.

The second feature I find is that this heterogeneity drives a wide variety of health care utilization behavior. To get an idea of what the results imply, Table 2.4 presents selected statistics for the top 5 types with the highest estimated mass. The most frequent type ($h = 1$) is the healthiest, but likes going to the doctor the most. Indeed, there is only 1 percent probability that this type ends the year with zero accumulated health care demand, despite being particu-

Figure 2.3: Estimated distribution of types



larly healthy (i.e., low mean of the shock ν). The second most common type is the sickest and the poorest, which results in a lower TAT, so it exceeds the cap with probability close to one even in the least generous plan. The third and fourth most common types are relatively healthy and have a strong distaste for going to the doctor, so they rarely have positive annual health care demand. The fifth type has the largest variance of the health shocks distribution, which implies a large dispersion in the distribution of annual health care demand.

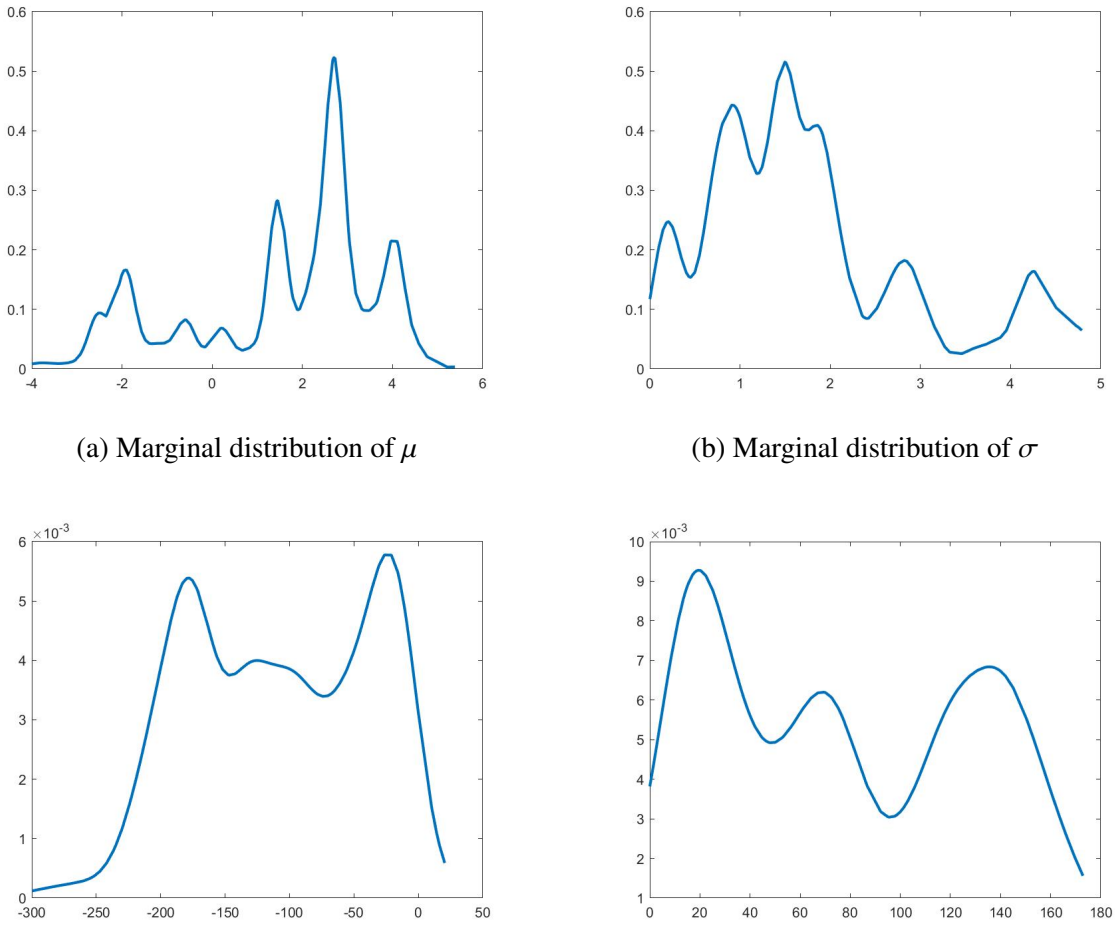
Table 2.4: Estimates of type weights

		Top 5 types				
		$h = 1$	$h = 2$	$h = 3$	$h = 4$	$h = 5$
	Mean of the shock, with $\lambda \sim LN(\mu_h, \sigma_h)$	11.24	66.73	22.85	61.22	54.28
	Standard deviation of the shock	20.4	162.4	24.4	11.0	376.2
	κ_h: shift of the LN distribution	-20.9	-132.8	-177.8	-203.0	-172.0
	ω_h: static moral hazard	17.7	72.4	121.0	140.0	141.9
	annual income$_h$	10,945	1,459	16,558	11,646	2,862
Free care plan	$\mathbb{E}$[annual utilization]: free	457	2,168	131	187	2,583
Least generous plan	$\mathbb{E}$[annual utilization]	231	2,161	1	0	2,509
	TAT: Total Annual Threshold	1,053	230	1,053	1,053	452
	$\mathbb{P}$[hit TAT]:	<0.001	0.995	<0.001	<0.001	0.742
	$\mathbb{P}$[annual utilization = 0]:	0.012	<0.001	0.989	1	0.061
	θ_h: type weight	0.13	0.10	0.10	0.06	0.05
	Characteristics	healthiest highest κ	sickest poorest	wealthiest	lowest κ	highest SD highest ω

In Figure 2.4, I present the estimated marginal distributions of unobserved heterogeneity. Overall, the estimates imply an average health risk $\mathbb{E}(\nu_t)$ of \$26.33 per family-week. I estimate an average price sensitivity parameter ω of \$26.89. I estimate large heterogeneity in both

health risk and price sensitivity. One standard deviation of expected health risk $\mathbb{E}(\nu_t)$ is equal to \$32.74, or a coefficient of variation of 1.24. Price sensitivity ω is also estimated to be highly heterogeneous, with a standard deviation across families of \$15.82, or a coefficient of variation of 0.59.

Figure 2.4: Estimated marginal distributions of unobserved type heterogeneity



(a) Marginal distribution of μ

(b) Marginal distribution of σ

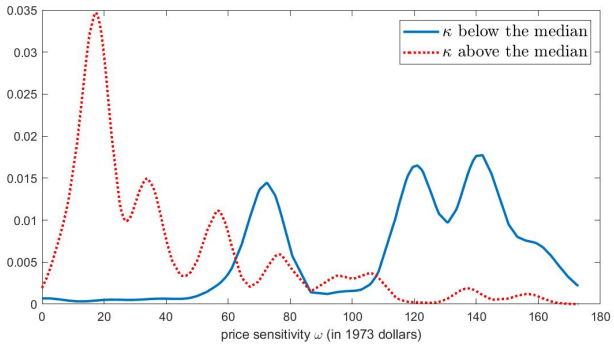
(c) Marginal distribution of κ

(d) Marginal distribution of ω

I also find that allowing for flexible-correlated heterogeneity is important. As an illustration, in Figure 2.5 I plot the price sensitivity ω separately for families with a low versus high preference for doctor visits (κ). First, there is a big range in terms of how price sensitive families are. Families increase their weekly health care utilization between 0 and 180 dollars when moved from no insurance to full insurance. Second, there is a strong negative correlation between price sensitivity and preference for doctor visits. Families who like to go to the doctor are less likely to increase spending due to moral hazard.

In Table 2.5, I report the unconditional correlations implied by the estimated type distri-

Figure 2.5: Price sensitivity ω, by preference for doctor visits κ



Price sensitivity ω, by preference for doctor visits κ

bution. As shown in Figure 2.5, the unconditional correlation between ω and κ is -0.41. I also find that the unconditional correlation between μ and σ is negative and sizeable (-0.45). This implies that the health shocks of sicker individuals are less volatile and more concentrated around the mean. However, this is only part of the picture. The correlation between μ and κ is also negative and important (-0.33). Thus, higher means of the normal distribution of $\log(\nu+\kappa)$ are also associated with higher shifts towards the left.

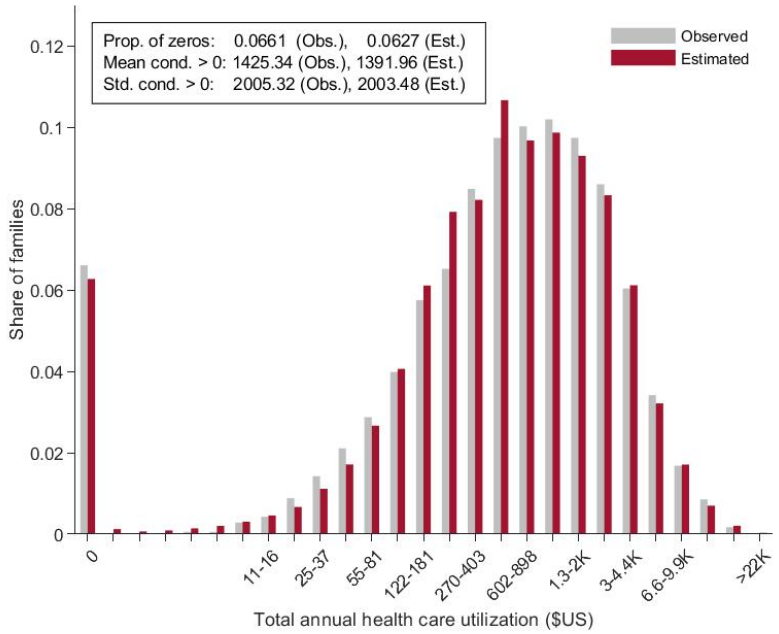
	μ	σ	κ	ω	income
μ	1.00	-0.45	-0.33	-0.26	0.31
σ	-0.45	1.00	0.08	0.30	-0.03
κ	-0.33	0.08	1.00	-0.41	-0.10
ω	-0.26	0.30	-0.41	1.00	-0.09
income	0.31	-0.03	-0.10	-0.09	1.00

Table 2.5: Unconditional correlations

2.6.2 Model Fit

Figure 2.6 reports the actual and predicted distributions of annual health care utilization for the overall sample. This measure includes both the portion paid out-of-pocket by the family (if any) and the portion covered by the insurance company. Overall, the fit is quite good. For example, actual average annual health care utilization is $1,188, while the estimate from the model is $1,217, a difference of 2 percent. The fraction of families who have zero annual health care demand is also tightly fitted, 0.066 in the data versus 0.063 in the model. This is a very nice feature of the model, since previous papers either abstract from the corner solution at zero or display poor fit on this dimension.

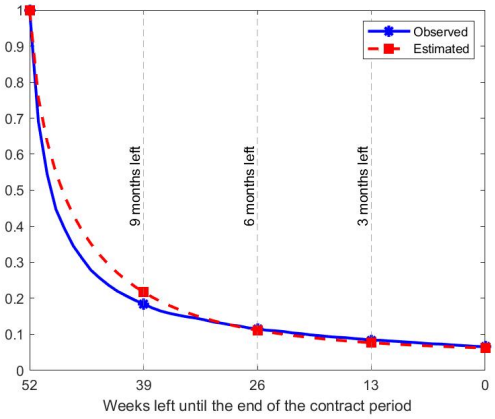
Figure 2.6: Observed and Estimated Distribution of Annual Health Care Utilization



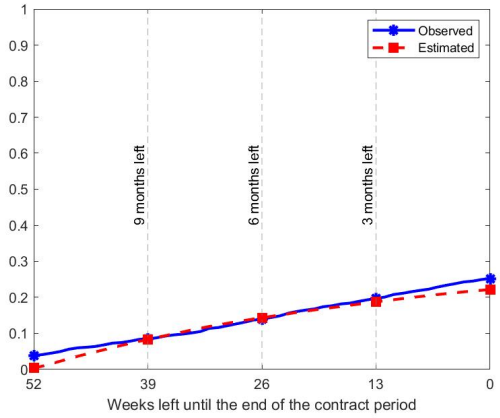
Notes: Observed (light) and estimated (dark) annual health care utilization in dollars. This figure uses a log scale: each bin $k = 1, \ldots, 26$ corresponds to utilization in the range $exp(0.4 \times (k-1)) - exp(0.4 \times k)$, with all utilization above $exp(0.4 \times 26) \approx 22K$ contained in last bin. The labels on the x-axis show the corresponding dollar amounts for each bin.

Figure 2.7(a) shows the observed and estimated proportion of families with zero accumulated health care demand as a function of weeks left until the end of the contract. Assessing whether the model is able to accurately replicate these proportions is key for studying the optimal resetting time for deductibles and caps, which I do in the following section. As can be seen, the model fits these proportions remarkably well. Figure 2.7(b) reports the observed and predicted probabilities of hitting the annual OOP limit by the beginning of each contract week for the overall sample. These moments are not targeted in the estimation procedure. The model fits these probabilities remarkably well.

Figure 2.7: Model Fit



(a) Proportion of families starting each contract week with zero accumulated health care consumption



(b) Proportion of families starting each contract week above the annual cap on OOP spending

2.6.3 Dynamic Moral Hazard Estimates

In my model, ω captures the full scope of moral hazard per week. The estimated average of ω_h is about \$77, which induces a 45 percent increase in annual utilization from no insurance to full insurance, relative to full insurance. However, knowing the full scope of moral hazard is not very useful for policy makers and contract designers given the wide popularity of nonlinear health insurance contracts. Under a typical nonlinear contract, forward-looking families internalize that current health care utilization reduces future expected prices. As a consequence, the distribution of ω does not provide a complete picture of moral hazard.

At the core of this paper is the concept of dynamic moral hazard. To disentangle the contribution of dynamic moral hazard to total moral hazard, I simulate the weekly health care

utilization behavior using my estimated model but assuming families behave myopically.[46] Under this assumption, families respond only to the current spot price of care, thus shutting down dynamic moral hazard.

The additional health care utilization due to the presence of dynamic moral hazard comes from two sources: (1) the difference in weekly utilization between myopic and forward-looking families in weeks in which both are below the cap, and (2) the difference in the number of weeks spent above the cap between myopic and forward-looking families. Equation (2.19) below shows these two sources, and a third scenario where dynamic moral hazard is zero because both the myopic family and its forward-looking counterpart are above the cap.

$$\text{Dynamic MH}_t = \begin{cases} \omega\delta \dfrac{\partial E[V_{t+1}(C_{t-1}+c_t, \nu_{t+1}; k)]}{\partial c_t} & , \quad \text{if} \quad C_t^{\text{myopic}} < TAT_k \quad \text{and} \quad C_t < TAT_k \\ \omega \dfrac{\partial OOP(c_t^{\text{myopic}}, C_{t-1}^{\text{myopic}}; k)}{\partial c_t^{\text{myopic}}} & , \quad \text{if} \quad C_t^{\text{myopic}} < TAT_k \quad \text{and} \quad C_t \geq TAT_k \\ 0 & , \quad \text{if} \quad C_t^{\text{myopic}} \geq TAT_k \quad \text{and} \quad C_t \geq TAT_k \end{cases} \tag{2.19}$$

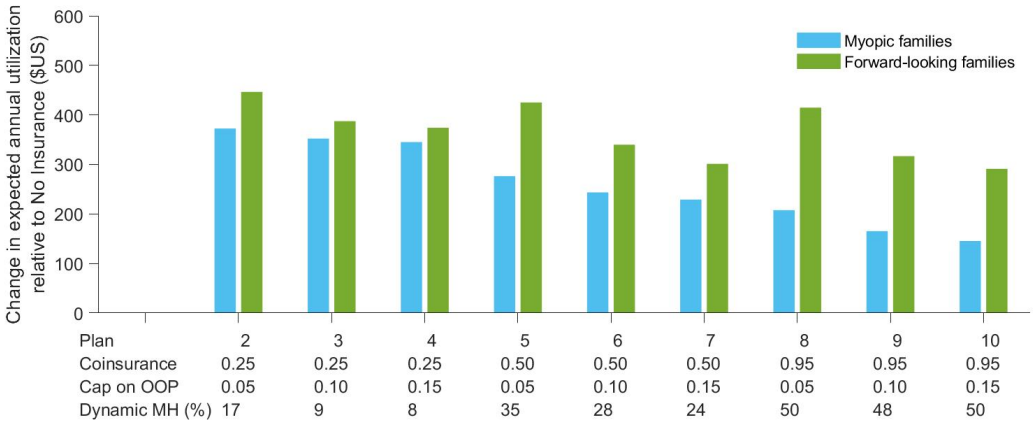
Using the estimated distribution of types in the overall sample, I simulate the behavior of forward-looking and myopic families. I decompose annual moral hazard in the portion explained by static moral hazard and the portion explained by dynamic moral hazard. As is standard in the literature, moral hazard is defined as the change in annual health care utilization in dollars relative to no insurance. To see the impact of different contract features on the importance of dynamic moral hazard, I perform this decomposition for each of the nonlinear experimental plans studied here.

Figure 2.8 shows the difference in average annual health care utilization comparing no insurance to one of the nonlinear experimental plans. Light-blue bars correspond to the estimates for myopic families while green bars correspond to forward-looking families. I list the plan features below the horizontal axis and the estimated contribution of dynamic moral hazard to total moral hazard in the last row. According to my estimates, dynamic moral hazard explains between 8 and 50 percent of total moral hazard, depending on the plan, and 40 percent on average across plans. Dynamic moral hazard is more important when [1] the coinsurance rate is higher, and [2] the cap on out-of-pocket spending is smaller. This is because lower caps are more likely to be reached and higher coinsurance rates increase OOP spending relative to total

[46] I randomly draw 20,000 sequences of 52 health shocks for each family type with estimated weight greater than or equal to 0.01 percent, i.e., $\widehat{\theta_h} \geq 0.0001$. I simulate the two models forward for each type and nonlinear plan in the sample. Then I average across the 20,000 simulations to compute annual health care utilization for myopic and forward-looking families for each type and plan.

utilization, which increase the likelihood of hitting the cap. This analysis highlights that health care utilization under plans with high coinsurance rates and/or low caps is particularly affected by the dynamic moral hazard. Abstracting away from these dynamic pricing incentives underestimates the cost from moral hazard, and may likely lead towards socially inefficient levels of coverage. In the next section I examine the impact of each contract feature thoroughly and study the mechanisms at play.

Figure 2.8: Dynamic Moral Hazard by Experimental Plan



2.7 Optimal Design of Employer-Sponsored Health Insurance

I now use my model and estimates to explore the impact of dynamic incentives and the associated dynamic moral hazard on welfare and optimal health insurance design. I do so in the context of employer-sponsored health insurance, in which a hypothetical employer offers a single plan in which all employees are enrolled. This allows me to focus on the welfare trade-off between risk protection and (static and dynamic) moral hazard across different plan structures, abstracting away from questions related to competition across plans. Moreover, this setting also describes a reasonable proportion of 43 percent in the U.S. population[47] and is consistent with recent papers finding that the optimal menu to offer features a single plan.[48] In the interest of exploring broader questions related to the current discussion about insurance market, the counterfactual analysis considers the impact of dynamic moral hazard outside the scope of the

[47]Proportion of employees in private-sector establishments offered only one health insurance option through their employer. Source: Agency for Healthcare Research and Quality, Medical Expenditure Panel Survey (MEPS) Insurance Component National-Level Summary Tables, 2020.

[48]See Ho and Lee (2020) and Marone and Sabety (2022).

plans offered in the RAND HIE. The contracts I study in this section vary across four features: (1) the size of the deductible, (2) the coinsurance rate after the deductible, (3) the cap on OOP spending, and (4) the resetting time for deductibles and caps.[49]

In order to rank alternative contracts, I follow the recent literature and use a measure of welfare that incorporates the benefits of risk protection and the social costs of utilization induced by insurance in a consistent framework.[50] In particular, I use the welfare metric from Einav, Finkelstein, Ryan, Schrimpf, and Cullen (2013) and extend the welfare decomposition in Marone and Sabety (2022) by incorporating the impact of dynamic moral hazard separate from traditional (i.e., static) moral hazard.

2.7.1 Measuring Welfare

Following Einav, Finkelstein, Ryan, Schrimpf, and Cullen (2013), I assume that families have constant absolute risk aversion (CARA) preferences and measure welfare using a certainty equivalent approach. This approach equates the expected utility for each health plan with a certain monetary payment at the beginning of the coverage year. Formally, for a family defined by the type vector $\boldsymbol{\beta}_h = (F_{\boldsymbol{\nu}}(.;h), \omega_h, \text{PY income}_h)$, the certainty equivalent to a plan j, e_{hj}, is determined by solving

$$-\exp(-\psi\, e_{hj}) = -\int \exp(-\psi\, u^{\star}(\boldsymbol{\nu};\boldsymbol{\beta}_h, j))dF_{\boldsymbol{\nu}}(\boldsymbol{\nu}), \tag{2.20}$$

where ψ is the annual coefficient of absolute risk aversion and $u^{\star}(.)$ is the maximum annual utility for a given sequence of realized health shocks $\boldsymbol{\nu}$.[51] The assumption of CARA preferences over the annual utility implies that (1) risk preferences only impact plan utilities but not within-the-year health care utilization decisions, and (2) family income does not impact relative plan

[49] Even though all plans in the RAND HIE feature zero deductibles, the 95 percent coinsurance plans in the study closely resemble the high-deductible catastrophic plans offered today (Brook, Keeler, Lohr, Newhouse, Ware, Rogers, Davies, Sherbourne, Goldberg, Camp, et al., 2006). Regarding the variation needed to study shorter resetting times for deductibles and caps, I leverage my within-year dynamic model of health care utilization, in which demand is affected by the number of weeks left in the contract, among other things. The key identifying variation comes from the variation in the proportion of families in the data that starts each contract week with zero accumulated health care utilization. For example, a family with zero accumulated health care demand at the beginning of contract week 27 is *de facto* facing a resetting time of six months.

[50] See e.g., Kowalski (2015), Ho and Lee (2020), and Marone and Sabety (2022).

[51] The risk aversion parameter is difficult to identify in the absence of insurance plan choice data. Hence, for the counterfactuals, I borrow from Einav, Finkelstein, Ryan, Schrimpf, and Cullen (2013) the estimate of the average coefficient of absolute risk aversion, $\psi = 0.0019$. This value implies that to make families indifferent between (i) a payoff of zero and (ii) an equal-odds gamble between gaining \$100 and losing \$X, the mean value of \$X is \$84.0.

utilities. Hence, the certainty equivalent for a type-h family and plan j can be written as:[52]

$$e_{hj}(\boldsymbol{\beta}_h) = -\frac{1}{\psi}\ln\Big[\int \exp(-\psi\,\widetilde{u}^{\star}(\boldsymbol{\nu};\boldsymbol{\beta}_h, j))dF_{\boldsymbol{\nu}}(\boldsymbol{\nu})\Big] + (Y_h - premium_j) \equiv \widetilde{e}_{hj}(\boldsymbol{\beta}_h) + (Y_h - premium_j), \tag{2.21}$$

where $\widetilde{e}_{hj}(\boldsymbol{\beta}_h)$ captures the family's welfare from coverage, and residual income, $Y_h - premium_j$, enters additively.[53] Using this notation, differences in $\widetilde{e}_h(.)$ across contracts with different coverages capture the willingness to pay for coverage. For example, a type-h family is willing to pay at most $\widetilde{e}_{hk}(\boldsymbol{\beta}_h) - \widetilde{e}_{hj}(\boldsymbol{\beta}_h)$ in order to increase its coverage from j to k.

I further assume that insurance providers are risk neutral. Thus, the provider's welfare when a type-h family is enrolled in contract j is given by his expected profits, or

$$\pi_{hj}(\boldsymbol{\beta}_h) = premium_j - \mathbb{E}_{\boldsymbol{\nu}}\Big[k_j(C_T^{\star}(\boldsymbol{\nu};\boldsymbol{\beta}_h, j))\Big], \tag{2.22}$$

where $C_T^{\star}(.)$ represents the optimal annual health care utilization and the function $k_j(.)$ maps this dollar amount to the portion covered by the provider under the rules of contract j.

Finally, the social welfare generated by allocating a type-h family to contract j is the sum of family and provider welfare. To define a measure of social welfare that does not depend on family income, I follow the literature (see e.g., Ho and Lee (2020) and Marone and Sabety (2022)) and measure social welfare relative to full insurance, which can be expressed as the difference between willingness to pay and expected insurer cost:[54]

$$RSS_{hj}(\boldsymbol{\beta}_h) = WTP_{hj}(\boldsymbol{\beta}_h) - \mathbb{E}_{\boldsymbol{\nu}}\Big[k_j(C_T^{\star}(\boldsymbol{\nu};\boldsymbol{\beta}_h, j)) - C_T^{\star}(\boldsymbol{\nu};\boldsymbol{\beta}_h, \text{full})\Big]. \tag{2.23}$$

To aggregate the welfare measure across all families according to a utilitarian social welfare function, I define the average relative social welfare across all families for contract j:

$$\overline{RSS}_j(\boldsymbol{\beta}, \boldsymbol{\theta}) = \sum_{h=1}^{H} \theta_h \times RSS_{hj}(\boldsymbol{\beta}_h). \tag{2.24}$$

Decomposition of Relative Social Welfare. I extend the discussion in Azevedo and Gottlieb (2017) and the generalization in Marone and Sabety (2022) and show that relative social wel-

[52] $\widetilde{u}^{\star}(\boldsymbol{\nu};\boldsymbol{\beta}_h, j) = \sum_{t=1}^{T}((c_t^{\star} - \nu_t) - \frac{1}{2\omega}(c_t^{\star} - \nu_t)^2 - OOP(c_t^{\star}, C_{t-1}; j))$.

[53] Equation (2.21) highlights that in this setup, the design of an optimal employer-sponsored insurance plan and the choice of how much to contribute towards employee premiums are separable problems for the employer, as long as employer contributions take the form of a fixed dollar amount.

[54] Note that because of the CARA assumption, premiums are transfers that do not affect social welfare.

fare, $RSS_{hj}(\boldsymbol{\beta}_h)$, can be decomposed in three terms: (1) the value of risk protection, (2) the social cost of *static* moral hazard, and (3) the social cost of *dynamic* moral hazard. This last component is novel to the literature and captures that a potentially important part of the welfare gains thought to be achieved by moving families away from full insurance are not actually realized because families anticipate reaching the deductible and/or the cap and adjust utilization accordingly.

The social welfare generated by allocating a type-h family to contract j (relative to allocating the same family to the free-care contract) can also be written as:

$$RSS_{hj}(\boldsymbol{\beta}_h) = \underbrace{\Psi(j,\boldsymbol{\beta}_h)}_{\substack{\text{Relative value of}\\ \text{risk protection}}} - \Bigg[\underbrace{\mathbb{E}_{\boldsymbol{\nu}}\Big[\sum_{t=1}^{T}\frac{\omega_h}{2}p^{\star}_{thj}(p^{\star}_{thj}-2)\Big]}_{\substack{\text{Relative social cost of}\\ \text{static moral hazard}}} + \underbrace{\mathbb{E}_{\boldsymbol{\nu}}\Big[\sum_{t=1}^{T}\frac{\omega_h}{2}\Big((\widetilde{sp}^{\star}_{thj}-1)^2-(p^{\star}_{thj}-1)^2\Big)\Big]}_{\substack{\text{Relative social cost of}\\ \text{dynamic moral hazard}}}\Bigg], \tag{2.25}$$

where $p^{\star}_{thj}$ represents the spot price of care and $\widetilde{sp}^{\star}_{thj}$ is the shadow price of care from equation (2.10), evaluated at the optimal health care utilization level.[55]

Premium Setting. As in Ho and Lee (2020), I require that insurance premiums cover families' total expected health care utilization, net of out-of-pocket payments that they make in the form of deductibles or coinsurance.[56]

Following the welfare decomposition in equation (2.25), three forces shape the design of health insurance contracts. Two of them are standard in the literature: risk protection and static moral hazard. In general, these forces go in opposite directions: more generous contracts provide higher protection against health risks but at the same time induce consumers to purchase additional care that they would not have bought had they faced the full cost. The third force is dynamic moral hazard, which is new to the discussion of how to manage the spending coverage trade-off. As the probability of exceeding the deductible/OOP limit increases, families internalize this and purchase more health care than they otherwise would. As I illustrate below, the presence of dynamic moral hazard can severely dampen the welfare gains associated with higher cost-sharing and plays a crucial role, distinct from static moral hazard, in determining optimal insurance contract design. In what follows, I analyze the deductible, coinsurance rate, OOP limit, and resetting time (for deductibles and OOP limits) that maximize average welfare when the employer only offers a single plan. I define the annual deductible in $250 increments

[55] In Appendix A.7, I provide details about how to arrive from the definition of relative social welfare in equation (2.23) to the decomposition in equation (2.25).

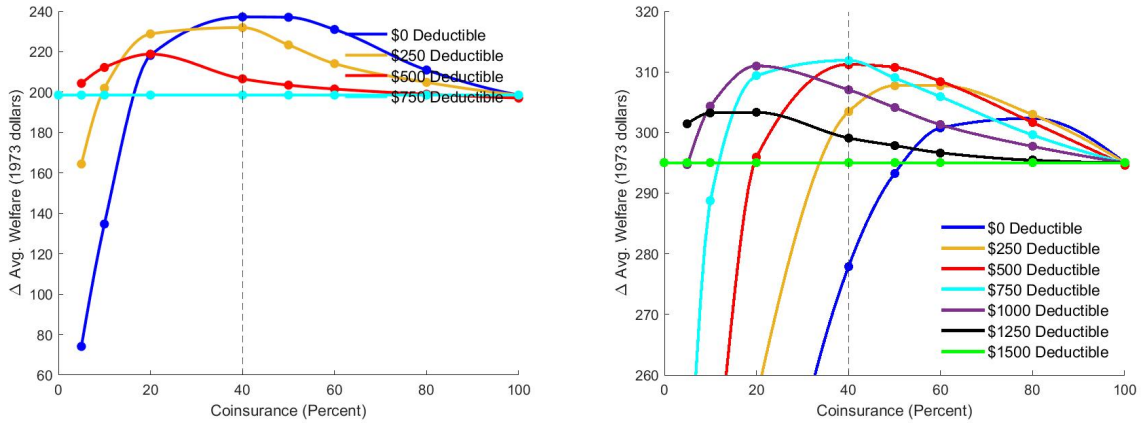
[56] These premiums are before loading costs. When loading costs are passed on to consumers, they are just transfers from the agents to the insurer. Therefore, loading costs do not affect average welfare.

between $0 and $2000, the level of coinsurance to vary from 0-100 percent in 10 percent increments, annual OOP maximum ranges from $0 (full insurance) to $2000 in $250 increments, and resetting times at either 3, 6, or 12 months. All dollar amounts are expressed in 1973 dollars.[57]

2.7.2 The determinants of the optimal deductible size

High deductible health plans have become increasingly common. In 2020, 31 percent of workers in the U.S. with employer-sponsored insurance were in such plans (Kaiser Family Foundation). To better understand the role played by the deductible, I fix the resetting time at the standard twelve-months level and study the optimal deductible size for different caps on OOP spending. I analyze two levels of OOP limits: a low-cap scenario, where I set the annual cap at $750, and a high-cap scenario, where I set the cap at $1500. In Figure 2.9, I plot the average social welfare from low-cap (left panel) and high-cap (right panel) plans with different deductible sizes as a function of the coinsurance rate, relative to full insurance. I find that under a low-cap plan, a zero-dollar deductible would be optimal, paired with a 40 percent coinsurance rate after the deductible. However, under a high-cap contract, a $750 deductible would be optimal, also paired with a 40 percent coinsurance rate after the deductible.

Figure 2.9: Change in Average Social Welfare, Relative to Full Insurance



(a) Low cap on OOP spending

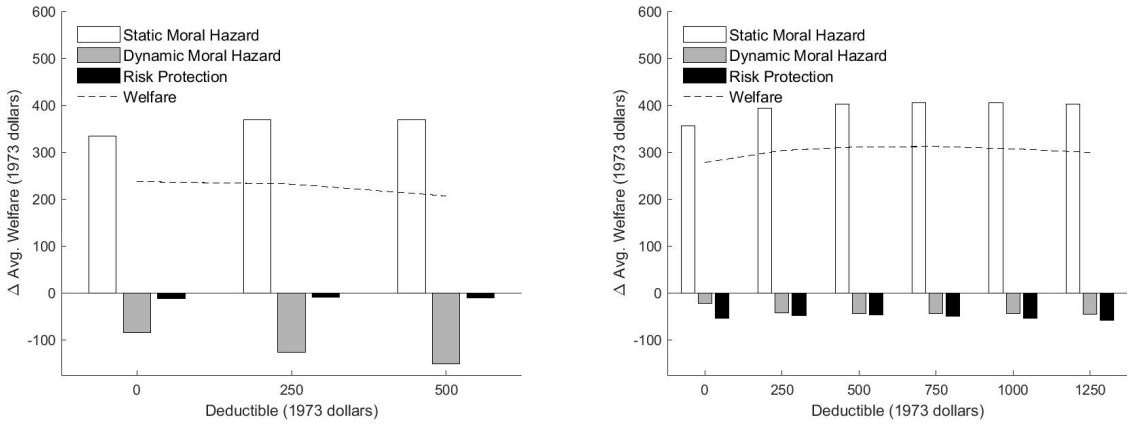
(b) High cap on OOP spending

To assess the role that each welfare component plays behind these findings, I fix the coin-

[57] I refer to deductibles and OOP limits corresponding to those in the metal-tiered plans (i.e., Gold, Silver, Bronze) offered on Affordable Care Act exchanges as "low", "middle", and "high", respectively. The deductibles, coinsurance rates, and out-of-pocket maximums in 2016 were $1,169, 21%, $2,564 for Gold; $3,060, 34%, $4,872 for Silver; and $5,771, 48%, $7,436 for Bronze. In 1973 dollars, the deductibles and out-of-pocket maximums are $210, $461 for Gold; $550, $876 for Silver; and $1,038, $1,337 for Bronze.

surance rate at 40 percent and take advantage of the welfare decomposition in equation (2.25). Figure 2.10(a) shows each welfare component as a function of the deductible size under the low-cap scenario. Clear bars represent the average welfare due to static moral hazard, relative to full insurance. Since full insurance is the most generous plan, this component is always non-negative. As one would expect, the gains from static moral hazard are increasing in the deductible as families bear a higher portion of the bill.

Figure 2.10: Welfare Decomposition Relative to Full Insurance



(a) Low cap on OOP spending

(b) High cap on OOP spending

Gray bars represent the average welfare due to dynamic moral hazard, relative to full insurance. This component is always non-positive under typical health insurance contracts, as consuming more today reduces future expected prices. It has the biggest gradient with respect to the deductible due to two mechanisms that reinforce each other. Higher deductibles increase OOP spending relative to total utilization, which increases the likelihood of hitting the cap. Forward-looking families respond by increasing utilization. In turn, both of these forces increase the expected number of periods spent above the deductible/cap which in turn increases utilization due to the lower prices faced after exceeding the deductible/cap. Therefore, a zero-dollar deductible, which minimizes these forces, achieves the minimum welfare loss due to dynamic moral hazard.

Lastly, black bars represent the average welfare due to risk protection, relative to full insurance. Since full insurance provides full protection against risks, this component is always non-positive. The loss due to decreased risk protection is small and roughly constant across deductible sizes because most of the risk protection comes from the low cap.

Combining the three welfare components, the dashed line represents average relative social welfare as a function of the deductible size. The big losses from dynamic moral hazard more

than offset the gains from static moral hazard as the deductible increases, which makes zero-dollar deductibles optimal under low-cap contracts. Average social welfare increases $237 per year relative to full insurance, which represents 16 percent of the annual premium in full insurance, and average annual health care utilization decreases 20 percent compared to full insurance. To further highlight that dynamic moral hazard plays a key role in making zero deductibles optimal under a low-cap scenario, I shut down dynamics and re-rank plans according to welfare. I find that a zero-dollar deductible is no longer optimal. The optimal deductible is $250, and even a $500 deductible achieves higher welfare than a zero deductible (absent dynamic moral hazard).

In contrast, for high caps on OOP spending, the optimal deductible size is no longer zero. Figure 2.10(b) presents the welfare decomposition for the high-cap scenario as a function of the deductible size. The main difference with the low-cap scenario is that under the high cap, the likelihood of hitting the cap is significantly smaller. This reduces the difference between the spot price and the shadow price, thus lowering the losses due to dynamic moral hazard, which were penalizing higher deductibles in the low-cap scenario. The losses from dynamic moral hazard are still increasing in the deductible, but smaller. The losses from decreased risk protection are more important now, and even bigger than the losses from dynamic moral hazard. As a result, the static moral hazard gains from higher deductibles drive the optimal deductible to $750. Social welfare is $312 higher and annual health care utilization is 33 percent lower compared to full insurance.

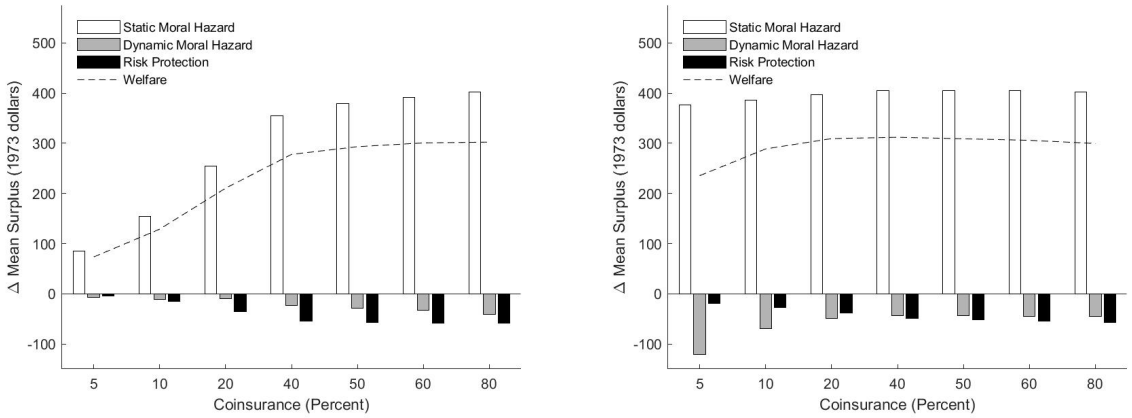
In summary, I find that zero-dollar deductibles are optimal for low to medium caps, while for high caps on OOP spending, high deductibles are welfare-maximizing. The first result coincides with the findings in Ho and Lee (2020), who focus on fairly generous (low) OOP maximums. The second result highlights that the optimal deductible size depends importantly on the cap on OOP spending, precisely due to the presence of dynamic moral hazard.

2.7.3 The determinants of the optimal coinsurance rate

To study how average welfare changes with the coinsurance rate, I continue to fix the resetting time at twelve months and set the cap at the high level ($1,500). Figure 2.11 depicts the welfare decomposition from equation (2.25) as a function of the coinsurance rate, under a zero-dollar deductible (left panel) and a high deductible ($750, right panel).

Under a zero-dollar deductible (Figure 2.11(a)), the gains from static moral hazard are increasing in the coinsurance rate because consumers' cost-sharing is increasing. The welfare losses from dynamic moral hazard are also increasing in the coinsurance rate, because higher

Figure 2.11: Welfare Decomposition Relative to Full Insurance



(a) Zero deductible

(b) High deductible

coinsurance rates allow forward-looking families to approach the cap at a faster rate. However, their magnitude is small due to the combination of zero deductible and high cap, and thus static moral hazard plays the dominant role. The losses due to decreased risk protection increase with the coinsurance rate as families pay a higher proportion out-of-pocket, but the magnitudes are also small relative to static moral hazard. Thus, static moral hazard drives the optimal coinsurance rate, which is 80 percent.

For the high-deductible scenario (Figure 2.11(b)), the picture is quite different. First, the gains from static moral hazard are significantly flatter across coinsurance rates, compared to the zero-deductible scenario. The reason is that the high deductible discourages health care demand, so even very low coinsurance rates after the deductible accrue big gains from static moral hazard. The loss in risk protection is increasing in the coinsurance rate, which pushes the optimal coinsurance rate down. However, for very low coinsurance rates, the losses due to dynamic moral hazard are now sizable. This is because now the dynamic moral hazard effect operates through two thresholds, the deductible and the cap, as opposed to just the cap in Figure 2.11(a). Under this new mechanism, low coinsurance rates make hitting the deductible very appealing. As a consequence, the shadow price decreases and utilization increases. The optimal coinsurance rate is 40 percent.

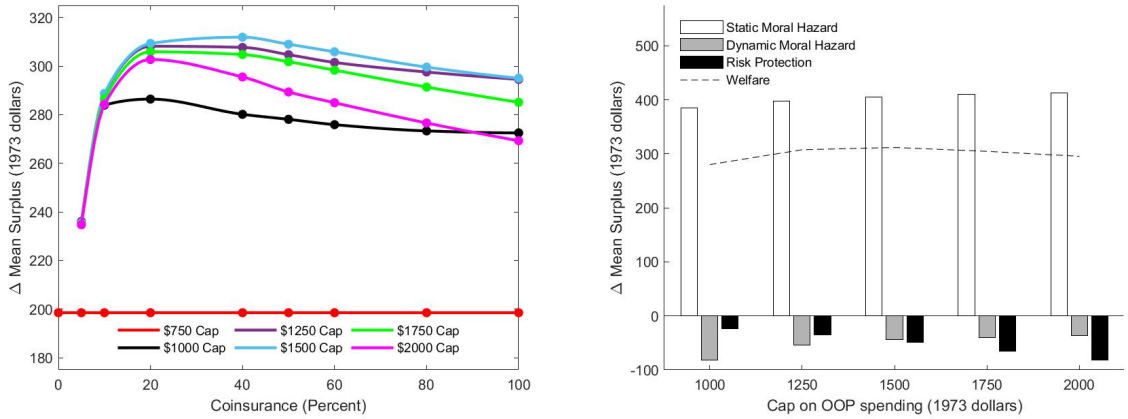
In summary, there are two main takeaways from this section. First, the optimal coinsurance rate and deductible are negatively related, as they are substitutes in providing the incentives to achieve welfare gains from static moral hazard, relative to full insurance. Second, under typical health insurance contracts that feature a deductible and a cap, dynamic moral hazard operates distinctively through these two thresholds. As a consequence, very low and very high

coinsurance rates exacerbate the losses from dynamic moral hazard.

2.7.4 The determinants of the optimal cap on OOP spending

I now turn to the determinants of the optimal cap on OOP spending again fixing the resetting time at twelve months. I only focus on the high-deductible ($750) scenario, but the results for other deductibles are similar both qualitatively and quantitatively. In Figure 2.12(a), I plot the average social welfare from high-deductible plans with different caps on OOP spending as a function of the coinsurance rate, relative to full insurance. The first takeaway is that pure stop-loss contracts[58] are never optimal, irrespective of the coinsurance rate (and the deductible size, not shown). This can be seen by comparing the welfare level of the straight horizontal line, with the other curves in the plot. The second takeaway is that the optimal cap on OOP spending lies within the range of high caps for all coinsurance rates, but not very high (below $1750). The optimum across coinsurance rates occurs at a cap of $1500.

Figure 2.12: Change in Average Social Welfare Relative to Full Insurance



(a) High deductible

(b) High deductible - 40 percent coinsurance rate

To unpack the contribution of each welfare component, I fix again the coinsurance rate at 40 percent, and present in Figure 2.12(b) the welfare decomposition as a function of the cap on OOP spending. The losses due to decreased risk protection are increasing in the cap since large caps leave families more exposed to health risks. Welfare gains from static moral hazard are also increasing in the cap because consumers' cost-sharing is increasing. Finally, the losses due to dynamic moral hazard are decreasing in the cap, as higher caps are less likely to be reached, thus decreasing the incentives to increase spending. Interestingly, the cap on

[58] Pure stop-loss contracts have no insurance up to a point, and full insurance thereafter, so that the deductible and the cap on OOP spending coincide.

OOP spending is the only contract feature for which the impact of static and dynamic moral hazard on welfare go in the same direction. This is why pure stop-loss contracts, in which the deductible and the cap coincide, are never optimal. Ultimately, the trade-off between net moral hazard and risk protection determines the optimal cap, achieved at $1500 (classified as high) under the high-deductible scenario.

So far I have studied the three popular cost-sharing features while fixing the resetting time at the standard twelve-months level. The overall optimal plan features a high deductible, 40 percent coinsurance rate after the deductible, and a high cap on OOP spending (equal to twice the deductible).[59] Under this optimal plan, average social welfare increases $312 per year relative to full insurance, which represents 21 percent of the annual premium under full insurance. Moreover, annual health care utilization is 33 percent lower compared to full insurance, on average.

2.7.5 Optimal resetting time for deductibles and OOP limits

Finally, I examine the impact of varying the timespan over which deductibles and OOP limits reset (six versus twelve months) holding fixed the contract length at the annual level. When I compare welfare between these policies, I adjust the deductible and cap proportionally to the resetting time. For instance, if I fix the standard deductible at $1000, I compare welfare between a $500 deductible that resets every six months and a $1000 deductible that resets every twelve months.

Shorter resetting times provide more risk protection through smaller caps. The consumers' financial losses from medium to severe health shocks are more likely to be capped under shorter resetting times.[60]

Different time aggregations of deductibles and caps may exacerbate or hinder the effect of static moral hazard. To understand the intuition, fix the deductible at zero and consider a plan with a six-months resetting cap of X dollars versus a plan with a standard cap of $2X$ dollars. During the first six months under both plans, a family in the resetting policy consumes (weakly) more health care due to static moral hazard than in the standard policy. This is mechanically driven by the smaller size of the resetting cap. However, during the second half of the contract year, this comparison is ambiguous. The resetting cap exacerbates the effect of static moral

[59] The optimal deductible size is consistent with the average family deductible in the so-called High-Deductible Health Plans (HDHP) in employer-sponsored settings in 2020, which was $4552 in 2020 dollars (or $752 in 1973 dollars). Source: Employer Health Benefits, 2020 Survey, Kaiser Family Foundation.

[60] In general, the financial losses from severe health shocks are equally likely to be capped under shorter or standard resetting times.

hazard in the second half of the year for relatively healthy families, while the opposite is true for relatively sick families. In total, which policy generates more overconsumption due to static moral hazard depends on the empirical joint distribution of health shocks.

Once we let families respond to the dynamic incentives, the effect of dynamic moral hazard can more than undo the negative difference in utilization between the resetting and standard policies during the first six months of the contract. This is driven by two mechanisms that reinforce each other. First, longer resetting times provide more opportunities to receive a health shock and consume health care that counts towards the cap. And second, the longer the resetting time for the cap, the more appealing it is to reach it soon because the family will enjoy free care for more periods.[61] As expected, these two mechanisms are more valuable to families who are relatively sick and/or more price sensitive (i.e., higher ω). As a consequence, this group of the population consumes more health care due to dynamic moral hazard under the standard policy.

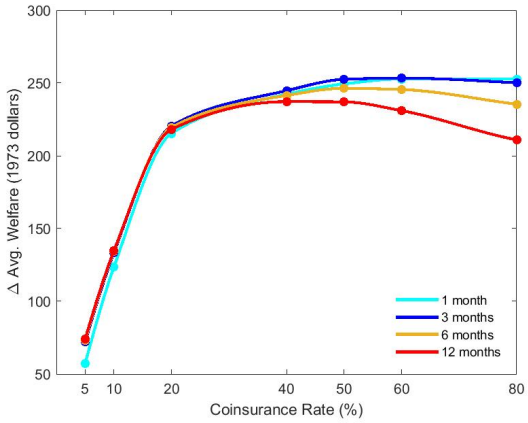
At the aggregate level, I find that the six-months resetting deductible policy is welfare-maximizing because it limits the escalation of dynamic moral hazard. Figure 2.13(a) shows the average welfare for pure-deductible plans as a function of the deductible size, relative to full insurance. The figure shows that the six-months deductible achieves higher welfare for all deductible sizes, on average. In Figure 2.13(b) I fix the annual deductible at \$500 (medium size) and plot the welfare decomposition from equation (2.25) for the two resetting policies. In this case, the gains from static moral hazard (clear bars) and the losses from risk protection (black bars) are similar between the two policies. However, the gray bars show that the twelve-months deductible is associated with bigger losses due to dynamic moral hazard, so the six-months deductible achieves higher welfare. In general, the gains from static moral hazard increase in the resetting time, while both the losses from dynamic moral hazard and the losses from risk protection worsen with the resetting time. This trade-off assures an interior solution for the optimal resetting time.

Longer resetting times induce bigger welfare losses due to dynamic moral hazard because families enjoy more periods above the deductible per year, on average. The longer the resetting time for the deductible, the more appealing it is to reach it soon because the family will enjoy the benefits of being above the deductible for more periods.[62] As a consequence, in the standard deductible policy, families spend more in health care when they are under the deductible, which puts them above the deductible proportionally earlier than in the six-months resetting policy,

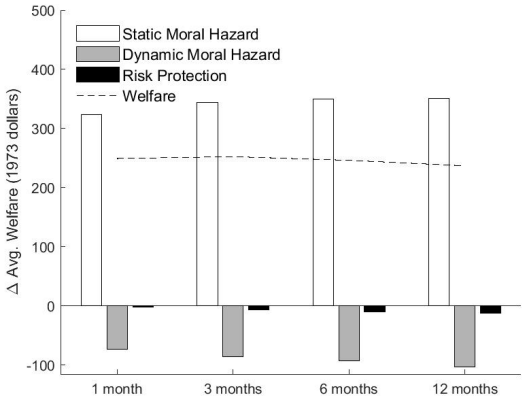
[61] Abstracting from truncation at zero, the utility function in equation (2.3) implies that for every period above the cap, a family enjoys positive utility equal to $\omega/2$.

[62] Abstracting from truncation at zero, the utility function in equation (2.3) implies that for every period above the cap, a family enjoys positive utility equal to $\omega/2$.

Figure 2.13: Welfare under deductibles that reset after six versus twelve months



(a) High deductible, high cap on OOP spending



(b) High deductible, high cap on OOP spending

enjoying more periods in free care. For example, families enjoy 10.4 weeks above the $500 deductible in the standard policy, and only 9.1 weeks above the $250 deductibles in total in the two consecutive six-months resetting policies. This behavior leads to bigger welfare losses from dynamic moral hazard in the twelve-months resetting deductible policy.

To summarize, I find that the optimal resetting time is heterogeneous across the distribution of health risks and that shorter-than-standard resetting times are associated with higher welfare precisely due to their smaller welfare losses from dynamic moral hazard. This last finding suggests that abstracting from dynamic moral hazard would favor longer resetting times, which may help reconcile why deductibles and OOP limits at shorter frequencies are not offered. Finally, whether or not different resetting times might coexist in the market would be an interesting avenue for further research.

2.8 Conclusion

In this paper, I study a new source of moral hazard that has been overlooked in most of the prior literature, mainly due to the use of annual models to study health care utilization decisions. I label this source as *dynamic* moral hazard to contrast with the traditional moral hazard present in static and annual models of health care demand. Under the typical nonlinear pricing scheme generated by the presence of deductibles and consumers' out-of-pocket limits in health insurance contracts, current health care utilization lowers future expected prices. Using data from the RAND Health Insurance Experiment, I show that families respond to these dynamic pricing incentives through two mechanisms: distance to the cap and time left until the contract

resets. I then build and estimate a dynamic model of health care demand that incorporates consumer heterogeneity along multiple and flexible-correlated dimensions. Using my model and estimates, I document that 40 percent of total moral hazard can be attributed to the dynamic moral hazard component.

Finally, I explore the impact of these dynamic incentives and the associated dynamic moral hazard on welfare and optimal health insurance design in the context of employer-sponsored health insurance. I show that the presence and significance of dynamic moral hazard have important implications, distinct from static moral hazard, for health care demand, optimal health insurance design, and costs of the health care sector. For example, a standard approach to curbing the social cost of moral hazard is to increase consumer cost sharing. Following this rationale, there is a recent trend towards offering high deductible plans. My results imply that introducing high deductibles is an efficient measure of cost containment only if the caps on consumers' out-of-pocket spending are not too close to the deductibles. Otherwise, dynamic moral hazard severely dampens the savings thought-to-be-achieved due to static moral hazard.

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Chapter 3

Multidimensional Unobserved Heterogeneity and Advantageous Selection in Health Insurance Markets

3.1 Introduction

Standard models of asymmetric information assume that potential insurance buyers have one-dimensional private information regarding their risk type. These models predict a positive correlation between insurance coverage and ex post realizations of loss. However, in some markets, such as life insurance (Cawley and Philipson, 1999), long-term-care insurance (Finkelstein and McGarry, 2006) and "Medigap" insurance (Fang, Keane, and Silverman, 2008), there is no empirical evidence of the positive correlation property. These findings point towards the existence of more than one dimension of unobserved heterogeneity and to the existence of at least one source of private information that is positively correlated with insurance coverage and at the same time negatively correlated with risk, which leads to "advantageous selection."[1]

In this paper, I study the evidence for and sources of advantageous selection in the context of health insurance for a general non-elderly population. I first propose a new method based on Revelt and Train (2001) to recover a family-specific distribution of multidimensional unobserved heterogeneity conditional on their health care utilization decisions and the estimated population distribution of types. The conditioning for individual families is important to differentiate potential insurance buyers effectively for pricing and/or marketing purposes and to im-

[1]The first description of this phenomenon in the economics literature dates back to Hemenway (1990), which used the term "propitious selection."

prove the predictions in new contract situations. I apply this method to rich data on within-year health care utilization decisions from The RAND Health Insurance Experiment, and quantify the fraction of unobserved heterogeneity that can be explained by observables typically used for pricing purposes and those related to health status. This provides an input to analyze selection and the plan portfolio design problem of employers, health insurance companies, and policymakers.

In tandem with these health care utilization data, I use the survey data on families' responses to hypothetical offers to purchase supplementary insurance coverage, also from The RAND Experiment. Using these insurance choice data and the dynamic structural model of Diaz-Campo (2021) to estimate within-year health care demand under different plan features, I recover a family-specific measure of risk aversion. Intuitively, a family's decision to choose a more (less) generous plan provides a lower (upper) bound for their coefficient of absolute risk aversion. With the risk aversion measure in hand, I examine the correlation between risk aversion and other dimensions of unobserved heterogeneity recovered from Diaz-Campo (2021) (e.g., health risk, propensity for moral hazard) to unmask potential sources of advantageous selection in health insurance markets.

Of considerable interest is the correlation between risk aversion and risk. On the theoretical side, De Meza and Webb (2001) propose that individuals have two dimensions of private information: their risk aversion and their risk type. Selection on risk aversion is advantageous if those who are more risk averse both buy more generous insurance and have lower risks. On the empirical side, there have been mixed results. For example, Cohen and Einav (2007) find that risk aversion has a strong positive correlation with risk in the auto insurance market, an appealing finding from a theoretical point of view as it retains a single crossing property, but contrary to what is required for risk aversion to be a source of advantageous selection. However, Cawley and Philipson (1999) find that the mortality rate of US males purchasing life insurance is below that of the uninsured and Finkelstein and McGarry (2006) find a negative correlation between risk aversion and health risk for the long-term care insurance market. More in line with Fang, Keane, and Silverman (2008), my results suggest that those who are more risk averse are not particularly healthy.

My analysis points to another potential source of advantageous selection: preferences for visiting the doctor. I find that higher preferences for going to the doctor, which would induce higher expected claims, are negatively correlated with risk aversion and, therefore, risk coverage. My results also provide evidence of *"selection on moral hazard"* in the spirit of Einav, Finkelstein, Ryan, Schrimpf, and Cullen (2013) or *"selection on unobserved anticipated effort"* from Karlan and Zinman (2009). In this sense, I find a strong positive correlation be-

tween risk aversion and propensity for moral hazard, suggesting that families would select insurance coverage in part based on their anticipated behavioral response to more generous insurance. Finally, I find that family income is negatively associated with absolute risk aversion, consistent with the findings of Cohen and Einav (2007) in auto insurance markets. This seems reasonable since high-income families can potentially self-insure against most health risks.

The remainder of this chapter is organized as follows. Section 3.2 describes the data and analysis sample. Section 3.3 outlines the methodology for recovering family-specific distributions of unobserved heterogeneity and risk aversion. Section 3.4 presents the main results and discusses the sources of advantageous selection. The last section concludes.

3.2 Data and Sample

I use rich, individual, line-item records as well as individual-level survey data from The RAND Health Insurance Experiment (hereafter, HIE). The RAND HIE is a randomized controlled trial to evaluate the effects of varying the generosity of insurance coverage. Details of the design of the study and the sample selection procedure have been given elsewhere (Diaz-Campo, 2021). Here I will note only a few of the central features of the study design and focus on the insurance choice data.

Families participating in the study were randomly assigned to an experimental insurance plan. The plans varied on two dimensions: the coinsurance rate (the share of the bill the family paid), and an upper limit on annual out-of-pocket expenditure. The coinsurance rates were 0 (or free care), 25, 50, or 95 percent. The maximum out-of-pocket expenditure, also called the Maximum Dollar Expenditure (MDE), was either 5, 10, or 15 percent of the family's income, and could not exceed $1,000. About 70 percent of families participated for three years, the rest for five years.

Because The RAND HIE randomly assigned families to insurance plans, I cannot recover risk aversion from plan enrollment. Instead, I use survey data on participating families' responses to hypothetical offers to purchase supplementary insurance coverage.[2] At the end of their participation, each family was presented with hypothetical offers to reduce the amount of its MDE. The offers stipulated a premium the family would have to pay for the supplementary insurance, and the family was asked whether it would buy the supplementary plan at the quoted premium. Each family received hypothetical offers to reduce the MDE by one-third, by

[2]Insurance preference questionnaires were given to all insured families, except those enrolled in the free-care plan and those who were terminated or attrited.

two-thirds, and by 100 percent (full coverage), with correspondingly higher premiums.

The offers were worded as follows:

> Suppose you were enrolled in a national health insurance plan just like the Family Health Protection Plan, and you had the same maximum dollar expenditure (MDE), which is $_____ per year for your family. If you could lower the MDE to $_____ by paying a fee of $_____ per year, would you do it or not?
>
> 1. Yes, I certainly would
> 2. I probably would
> 3. I probably would not
> 4. No, I certainly would not

The premiums quoted for each offer were randomly generated using an algorithm designed to produce premium quotes ranging from 10 percent of the change in MDE to almost 100 percent of the change.[3] Out of the 1,335 families presented with hypothetical offers, only 1,084 families pass the sample inclusion criteria and are the subject of the insurance choice analysis here.[4] Table 3.1 characterizes the sample by plan, questionnaire completeness status, and responses to the three hypothetical offers.

3.3 Methodology

In this section, I first introduce the methodology to recover family-specific distributions of health status, preferences for going to the doctor, and propensity for moral hazard by extending the "conditioning of individual taste" method from Revelt and Train (2001). Second, I explain how to use the structural model from Diaz-Campo (2021) and the health insurance choice data from The RAND HIE to recover a family-specific measure of risk aversion.

3.3.1 Recovering family-specific distributions of unobserved heterogeneity

The goal of the main estimation is to recover the distribution of types. There are two ways to view this distribution. The first is to assume each family belongs to exactly one type and that

[3] Premium computation is described in Appendix B of Marquis and Phelps (1985).

[4] The 251 families excluded belong to the so-called mixed plans, which have different coinsurance rates for different types of services.

Table 3.1: Sample for the analysis of insurance choice

	Health insurance choice	
	Families	Observations
Panel A: Plan		
25% coinsurance rate	336	992
50% coinsurance rate	204	597
95% coinsurance rate	544	1,557
Panel B: Questionnaire status		
All 3 scenarios completed	1,038	3,114
Only 2 scenarios completed	4	8
Only 1 scenario completed	24	24
No scenario completed	18	0
Panel C: Insurance choice		
"No" to all non-missing scenarios	490	1,452
At least one "Yes" and one "No"	338	1,012
"Yes" to all non-missing scenarios	238	682
Missing all 3 scenarios	18	0
Total	1,084	3,146

with enough data this type will be revealed. Alternatively, we could assume that each family is itself a mixture of types, either because the family consists of several members or because a given individual's behavior is best described as a mixture of types. In this case, even with unlimited data, the distribution of types for each family will not be degenerate. Nevo, Turner, and Williams (2016) does not take a stand on which is the correct view since ultimately only the aggregate distribution of types is of their interest. However, when the focus is on recovering family-specific types, distinguishing between these two views is important. I assume here the first view is the correct, so that each family belongs to exactly one type and with unlimited data this type would be revealed.

Let the vector $\boldsymbol{\beta} = \{\mu, \sigma, \kappa, \omega, \text{py income}\}$ collect the dimensions of unobserved heterogeneity. The first three elements govern the mean, standard deviation, and shift of the log-normal distribution of weekly health shocks, respectively. The fourth element, ω, represents the weekly propensity for moral hazard. The last element, py income, describes the family's previous year income, which affects the family-specific MDE. Let the density $g(\boldsymbol{\beta}|\hat{\boldsymbol{\theta}})$ describes the estimated distribution of types in the population, hereafter "the prior." The vector $\hat{\boldsymbol{\theta}}$ collects the estimated weight of family type h characterized by the vector of unobserved heterogeneity β_h, with $h = 1, \ldots, H$. I want to determine where each family's $\boldsymbol{\beta}$ lies in this distribution. I

infer information about each family's $\boldsymbol{\beta}$ by conditioning on the family's observed outcomes (plan enrollment, k, and sequence of health care utilization choices, $\boldsymbol{c}$). Let $h(\boldsymbol{\beta}|k, \boldsymbol{c}, \hat{\boldsymbol{\theta}})$ denote the density of $\boldsymbol{\beta}$ conditional on the family's observed outcomes in addition to the estimated distribution of types in the population, hereafter "the posterior." Using the "conditioning of individual tastes" method from Revelt and Train (2001), I recover families' posterior distribution of $\boldsymbol{\beta}$ by Bayes' rule:

$$h(\boldsymbol{\beta}|k, \boldsymbol{c}, \hat{\boldsymbol{\theta}}) = \frac{Prob(\boldsymbol{c}|k, \boldsymbol{\beta}) \cdot g(\boldsymbol{\beta}|\hat{\boldsymbol{\theta}})}{Prob(\boldsymbol{c}|k, \hat{\boldsymbol{\theta}})}. \tag{3.1}$$

Let c_t denote the family's health care utilization choice in period t, and let $\boldsymbol{c} = (c_1, \ldots, c_T; k)$ denote the family's sequence of health care utilization choices within a contract year indexed by the family's health insurance plan k. The probability of the family's observed outcomes, conditional on $\boldsymbol{\beta}$, is the product of likelihoods:

$$Prob(\boldsymbol{c}|k, \boldsymbol{\beta}) = LL(c_1; k|C_0, \boldsymbol{\beta}) \cdot \ldots \cdot LL(c_t; k|C_{t-1}, \boldsymbol{\beta}) \cdot \ldots \cdot LL(c_T; k|C_{T-1}, \boldsymbol{\beta}), \tag{3.2}$$

where $LL(c_t; k|C_{t-1}, \boldsymbol{\beta})$ is the probability that the family chooses c_t when enrolled in health insurance plan k conditional on accumulated health care utilization C_{t-1} and type characterized by the vector $\boldsymbol{\beta}$. The within-year dynamic model of health care utilization choices from Diaz-Campo (2021) predicts that upon realizing their health state ν_t, families choose period-t health care utilization c_t by trading off the (current and future) benefits of health care utilization with its current out-of-pocket cost. Specifically, accounting for the fact that negative health states may imply zero health care utilization, the model predicts optimal health care utilization $c_t^\star(\nu_t, C_{t-1}; \boldsymbol{\beta}, k) = \max[0, \nu_t + \omega \cdot (1 - \widetilde{sp}_t(c_t^\star, C_{t-1}; \boldsymbol{\beta}, k))]$ for a family characterized by $\boldsymbol{\beta}$ enrolled in plan k, where $\widetilde{sp}_t(\cdot)$ is the shadow price of care. Inverting the expression, the health state realization $\nu_{tkr}(\boldsymbol{\beta})$ that would have given rise to observed utilization c_t under unobserved heterogeneity $\boldsymbol{\beta}$ is given by

$$\nu_{tkr}(\boldsymbol{\beta}) : \begin{cases} \nu_{tkr} \leq -\omega \cdot (1 - \widetilde{sp}_t(c_t^\star, C_{t-1}; \boldsymbol{\beta}, k)) & c_t = 0 \\ \nu_{tkr} = c_t - \omega \cdot (1 - \widetilde{sp}_t(c_t^\star, C_{t-1}; \boldsymbol{\beta}, k)) & c_t > 0. \end{cases}$$

Family health state is distributed according to

$$\log(\nu_t - \kappa) \sim N(\mu, \sigma^2).$$

There are two possibilities to consider. First, if c_t is equal to zero, the implied health state realization ν_{tkr} is not only negative but also smaller than the negative value of the extra health care utilization due to moral hazard. Second, if c_t is greater than zero, the implied health state

realization ν_{tkr} is the difference between c_t and the extra health care utilization due to moral hazard. Taken together, the probability density of period-t health care utilization c_t conditional on plan and unobserved heterogeneity $\boldsymbol{\beta}$ is given by

$$LL(c_t; k|C_{t-1}, \boldsymbol{\beta}) = \left[\Phi\Big(\frac{\log(\nu_{tkr} - \kappa) - \mu}{\sigma}\Big)\right]^{\mathbb{I}(c_t=0)} \cdot \left[\Phi'\Big(\frac{\log(\nu_{tkr} - \kappa) - \mu}{\sigma}\Big)\right]^{\mathbb{I}(c_t>0)}$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function.

Finally, the probability of the family's observed outcomes conditional only on the estimated distribution of types in the population is obtained by integrating over all possible values of $\boldsymbol{\beta}$ as follows

$$Prob(\boldsymbol{c}|k, \hat{\boldsymbol{\theta}}) = \int Prob(\boldsymbol{c}|k, \boldsymbol{\beta}) \cdot g(\boldsymbol{\beta}|\hat{\boldsymbol{\theta}}) \cdot d\boldsymbol{\beta}. \tag{3.3}$$

3.3.2 Recovering family-specific measures of risk aversion

The expected utility of an observed family of unobserved type h with initial income I for contract k at premium p_k is given by $U(k, p_k, h)$, defined as

$$U(k, p_k, h) = \mathbb{E}_{\nu}\Bigg[- \exp\Bigg(- \psi\Big(I - p_k + \sum_{t=1}^{T_k}\Big[c_t - \nu_t - \frac{1}{2\omega}(c_t - \nu_t)^2 - OOP(c_t, C_{t-1}; k)\Big]\Big)\Bigg)\Bigg], \tag{3.4}$$

where ψ is a coefficient of absolute risk aversion. When a type-h family with initial income I is faced with the option between a contract k at premium p_k and a more generous contract j at a premium p_j, with $p_j > p_k$, the family chooses the contract that maximizes expected utility. If the family chooses the less generous option k, I find an upper bound for the type-specific risk aversion measure ψ, denoted $\overline{\psi_h}$, since a higher ψ would imply more risk aversion and higher willingness to purchase the more generous option j. If the family chooses the more generous option j instead, I find a lower bound for ψ, denoted $\underline{\psi_h}$.

As described in section 3.2, each family was presented with three hypothetical insurance choice situations. In the ideal case where the family answered at least one "Yes" and one "No", I can bound the family-specific measure of risk aversion both from below and above. For this case, I take the midpoint between $\underline{\psi_h}$ and $\overline{\psi_h}$ to be the risk aversion. If the family answered "No" to all hypothetical offers, then I take the midpoint between 0 and $\overline{\psi_h}$ to be the risk aversion. Finally, if the family answered "Yes" to all hypothetical offers, then I define $\underline{\psi_h}$ to be the risk aversion.

In order to compute the expected utility for each family under each choice situation, I

first re-solve the dynamic model of health care utilization for each family type under each hypothetical health insurance features as well as under the actual health insurance plan of the family at the time of exit. Second, I find the risk aversion level that would make each family type indifferent between the actual plan and each of the three hypothetical plans. Third, I define whether this risk aversion level of indifference is a lower or an upper bound, based on the family's choices. Finally, I use the family-specific posterior distribution $h(\boldsymbol{\beta}|k, \boldsymbol{c}, \hat{\boldsymbol{\theta}})$ to weight the contribution of each type and obtain a family-specific measure of risk aversion.

3.4 Empirical Results

3.4.1 Unobserved heterogeneity explained by observables

In order to design and price different plans to different groups of people, ideally insurers would like to recover the underlying type of potential enrollees using observed variables. In what follows I show how much of the unobserved heterogeneity can be explained by some observed variables that are thought to influence health care utilization decisions. In particular, the analysis will consider separately how the prediction improves when using observed variables that can be used for pricing purposes versus those that cannot be used for pricing.

As a benchmark, I start by assuming that in the worst case scenario, the insurance company only has access to a prior distribution of types that does not vary across observed characteristics. In the best case scenario, the company has access to the family-specific posterior distribution of types. In order to quantify the distance between the prior and the family-specific posterior distributions, I use the measure of Squared Euclidean Distance (SED). In particular, the SED for family i is defined as

$$SED_i^{\text{prior-post}} = \sum_{h=1}^{H} \left[g(\boldsymbol{\beta}_h|\hat{\boldsymbol{\theta}}) - h(\boldsymbol{\beta}_h|k_i, \boldsymbol{c}_i, \hat{\boldsymbol{\theta}}) \right]^2 \tag{3.5}$$

In order to predict the type distribution of a potential enrollee, I propose to regress the family-specific posterior distribution of types on several observed variables. Then, I predict the probability that a family with the given observed variables is of a particular type. In particular,

I propose the following series of linear regressions:

$$\begin{aligned} h(\boldsymbol{\beta}_1|\boldsymbol{c}_i, \hat{\boldsymbol{\theta}}) &= \alpha_1 X_i + \epsilon_{1i}, \qquad i = 1, \ldots, N \\ h(\boldsymbol{\beta}_2|\boldsymbol{c}_i, \hat{\boldsymbol{\theta}}) &= \alpha_2 X_i + \epsilon_{2i}, \qquad i = 1, \ldots, N \\ &\vdots \\ h(\boldsymbol{\beta}_H|\boldsymbol{c}_i, \hat{\boldsymbol{\theta}}) &= \alpha_H X_i + \epsilon_{Hi}, \qquad i = 1, \ldots, N \end{aligned}$$

To evaluate how much information we have learned with this prediction, I compute the SED between the family-specific predicted and posterior distributions as follows

$$SED_i^{\text{pred-post}} = \sum_{h=1}^{H} \left[\hat{h}(\boldsymbol{\beta}_h|k_i, \boldsymbol{c}_i, \hat{\boldsymbol{\theta}}) - h(\boldsymbol{\beta}_h|k_i, \boldsymbol{c}_i, \hat{\boldsymbol{\theta}})\right]^2, \tag{3.6}$$

and finally compare this measure with the benchmark SED from Equation (3.5) in order to quantify what fraction of the total distance between prior and posterior can be explained by observed variables. To measure this explained fraction, I propose two measures, one at the individual level and one at the aggregate level:

$$Explained_i = 1 - \frac{SED_i^{\text{pred-post}}}{SED_i^{\text{prior-post}}} \qquad \text{and} \qquad \overline{Explained} = 1 - \frac{\sum_{i=1}^{N} SED_i^{\text{pred-post}}}{\sum_{i=1}^{N} SED_i^{\text{prior-post}}}.$$

The interpretation of the fraction explained is similar to the R^2 of a linear regression. If the distance between the prior and family-specific posterior distributions is similar to the distance between the family-specific predicted and posterior distributions, this means that the regressors included are not providing useful information, so the fraction explained will be close to zero.

Table 3.2 shows the results of this exercise. Focusing on the last column, I find that about 5 percent of the distance between prior and posterior distributions can be explained by observables typically used for pricing purposes. In particular, I included age, number of family members and smoking behavior status. In the second row of the table, I added variables related with the health status of the family: an index of general health, number of disease conditions, activity limitations, etc. Now I can explain almost 40 percent of the distance between prior and posterior distributions of type. The main takeaway is that there is a substantial fraction of unobserved heterogeneity that can potentially be captured by observed variables from an ex-ante perspective. This information would allow insurers to design different plans for different groups of people based on observables they can condition on.

Table 3.2: Fraction of the distance between prior and posterior distributions of types explained by observables

		Families	$\overline{Explained}$
1	Age, family members, smoking behavior	3,560	0.0495
2	Add variables related to health status	2,371	0.3871

3.4.2 Family-specific risk aversion and advantageous selection

Table 3.3 shows the mean risk aversion by families' responses to the hypothetical offers.[5] Case 1 refers to families who answered "No" to all hypothetical offers, providing only an upper bound for their risk aversion. In this case, I define the midpoint between zero and this upper bound to be the measure of risk aversion. Case 2 refers to families who answered at least one "Yes" and one "No" to the hypothetical offers, providing both lower and upper bounds for their risk aversion. In this ideal case, I take the midpoint between these two bounds to be their risk aversion measure. Finally, case 3 refers to families who answered "Yes" to all hypothetical offers, providing only a lower bound for their risk aversion. For this case, I take this bound itself as their risk aversion measure. Since these cases are ordered in increasing level of risk aversion, reasonable values for the mean risk aversion would be increasing from case 1 to 3. This is what we observe in the last column of the table.

Table 3.3: Mean risk aversion by families' responses to the hypothetical offers

Case	Answers	Families	Formula for ψ	Mean ψ
1	"No" to all non-missing scenarios	490	midpoint in $[0, \overline{\psi}]$	0.0021
2	At least one "Yes" and one "No"	338	midpoint in $[\underline{\psi}, \overline{\psi}]$	0.0077
3	"Yes" to all non-missing scenarios	238	$\underline{\psi}$	0.0100
Total		1,066		0.0057

My estimates imply an overall mean (median) coefficient of absolute risk aversion of 0.0057 (0.0021). Put differently, to make families indifferent between (i) a payoff of zero and (ii) an equal-odds gamble between gaining \$100 and losing \$X, the mean (median) value of \$X is \$63.4 (\$82.4).[6] As emphasized by Einav, Finkelstein, Ryan, Schrimpf, and Cullen (2013), the estimated level of risk aversion is not directly comparable to most existing estimates. In my

[5] I treat option 1 *"Yes, I certainly would"* as a "Yes" answer, and all other responses as "No" answers. Similar results were obtained when I treat responses of *"Yes, I certainly would"* and *"I probably would"* as indicating an intention to purchase. See Appendix B.1.

[6] A risk-neutral family would have \$X equal to \$100, and an infinitely risk-averse family would have \$X equal to \$0.

model, realized utility is a function of both health risk and financial risk, while in other papers that estimate risk aversion from insurance choices (e.g., Cohen and Einav 2007) realized utility is only over financial risk.

The last step of my analysis is to examine the relationship between a family's risk aversion measure and the other dimensions of unobserved heterogeneity: health risk, preferences for going to the doctor, and propensity for moral hazard. I therefore estimate separate regressions of each dimension of unobserved heterogeneity on risk aversion. Table 3.4 presents the results for an indicator variable of risk aversion above the median and Table 3.5 for the risk aversion measure in levels. The dependent variable in column (1) is *HealthRisk*, which represents the expected weekly health care utilization in dollars under no insurance. This measure of health risk is governed by the mean μ and variance σ^2 of the underlying normally-distributed health shock. It is purged from the impact of moral hazard on health care utilization, as I assume no insurance to compute it.[7] In order to obtain a family-specific measure of health risk, I compute a weighted average across types using the family-specific posterior distribution of types. Similarly, the dependent variables in columns (2) to (4) are the family-specific weighted averages across types of the dimensions of unobserved heterogeneity captured by κ, ω, and py income, respectively.

Table 3.4: Regression coefficients of each dimension of unobserved heterogeneity on the indicator variable for absolute risk aversion above the median

	(1) *HealthRisk*	(2) *PrefDoctor*	(3) *MoralHazard*	(4) *Income*
RiskAversion above median	-19.53	-34.01***	52.06***	-5480.78***
	(11.67)	(3.02)	(1.84)	(325.67)
R^2	0.00	0.12	0.45	0.23
Number of families	968	968	968	968

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Option 1 (*Yes, I certainly would*) is classified as a "Yes" answer, and therefore determines a lower bound for risk aversion. Options 2 (*I probably would*), 3 (*I probably would not*), and 4 (*No, I certainly would not*) are classified as "No" answers, and therefore determine an upper bound for risk aversion.

According to the results of column (1) in both tables, I find a weak negative correlation to no correlation between risk aversion and health risk. Column (2) shows a negative correlation between risk aversion and preferences for visiting the doctor. This implies that people who like to visit the doctor are less risk averse. This negative relationship points to a potential source of

[7] Under the assumption that health shocks are log-normally distributed with underlying mean μ and variance σ^2, I define the type-specific measure of health risk under no insurance as $HealthRisk = \exp(\mu + 0.5\sigma^2)$.

advantageous selection, since higher preferences for visiting the doctor, which would typically induce more health care utilization, would be negatively correlated with insurance coverage. The results in column (3) show a strong positive correlation between risk aversion and the propensity for moral hazard. This is consistent with the findings from Einav, Finkelstein, Ryan, Schrimpf, and Cullen (2013) and points to the evidence of *"selection on moral hazard."* Finally, the last column shows a negative correlation between risk aversion and family income. This is reasonable since high-income families can potentially self-insure against most health risks, and is consistent with the findings of Cohen and Einav (2007) in the auto insurance market.

Table 3.5: Regression coefficients of each dimension of unobserved heterogeneity on the continuous measure of absolute risk aversion

	(1) *HealthRisk*	(2) *PrefDoctor*	(3) *MoralHazard*	(4) *Income*
RiskAversion	38.28	-223.24*	284.37***	-45386.77***
	(346.99)	(95.19)	(73.30)	(10900.43)
R^2	0.00	0.01	0.01	0.02
Number of families	968	968	968	968

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Option 1 (*Yes, I certainly would*) is classified as a "Yes" answer, and therefore determines a lower bound for risk aversion. Options 2 (*I probably would*), 3 (*I probably would not*), and 4 (*No, I certainly would not*) are classified as "No" answers, and therefore determine an upper bound for risk aversion.

3.5 Conclusion

Recovering rich and flexibly-correlated unobserved heterogeneity in several dimensions allows me to study the evidence for and potential sources of selection, both adverse and advantageous, and the scope for selection on moral hazard. In this paper, I propose a method to recover the distribution of multidimensional unobserved heterogeneity at the family level using the observed health care utilization decisions and a prior distribution of types in the population. Using survey data on families' responses to hypothetical offers to purchase supplementary insurance coverage, I recover a family-specific measure of risk aversion and study the correlation between risk aversion and other dimensions of private information.

According to my results, there is a weak negative correlation between risk aversion and health risk, that could be exploited as a source of advantageous selection. I also find a second

potential source of advantageous selection: preferences for going to the doctor. Higher preferences for visiting the doctor are positively correlated with health care utilization but negatively correlated with risk aversion and, therefore, risk coverage. Finally, my results provide further evidence of selection in moral hazard in the spirit of Einav, Finkelstein, Ryan, Schrimpf, and Cullen (2013).

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Chapter 4

The Effect of Maternity Conditional Cash Transfers on Abortion Decisions: Evidence from Argentina

4.1 Introduction

Conditional cash transfer programs (CCTs) shape the current social protection landscape in Latin America and the Caribbean and are also becoming prominent in other parts of the world, such as Asia and Africa, and even in higher-income countries such as Turkey and the United States. Their design and implementation vary across countries, but the programs typically provide cash transfers to families (usually mothers) in exchange for their engaging in behaviors that promote investments in child health and education. In an attempt to improve maternal and neonatal health by encouraging the use of adequate and timely prenatal care, several countries target their CCTs at pregnant women. While there is some evidence on the effect of these programs on prenatal health care utilization and birth outcomes, there is as yet no evidence on their impact on pregnant women's decisions between abortion and childbirth. The paucity of evidence is driven by a lack of data, primarily due to the illegal nature of the practice of abortion in most countries and the stigma associated with this practice in countries where it is permitted.

This paper estimates the causal impact of the Argentinean CCT *Asignación por Embarazo para Protección Social* on abortion decisions and children's birth outcomes. The program was implemented in May 2011 and targeted to pregnant women who are unemployed or working in the informal sector. We exploit the substantial amount of inflation in Argentina to instru-

ment for the endogenous participation in the program. We estimate that participation in the program led to a sizable reduction in the probability of abortion and in the incidence of normal birthweight (i.e., greater than 2,500 grams). These findings are consistent with a change in composition effect, in which mothers whose abortion decision is affected have a higher risk of low birthweight children.

A large literature explores the impact of CCTs on children's education, health, nutrition, and household-level poverty related outcomes (see Rawlings and Rubio (2005) and Fiszbein and Schady (2009) for a review). There is a narrower literature studying the impact of CCTs for pregnant women, focusing mainly on the demand for prenatal care, the probability of skilled assistance at birth, and birthweight. For example, regarding demand for prenatal care, Díaz and Saldarriaga (2019) find that the Peruvian CCT JUNTOS increased prenatal care utilization among program-eligible women. With respect to birth outcomes, Amarante, Manacorda, Miguel, and Vigorito (2016) estimate that participation in a similar program in Uruguay led to a sizable reduction in the incidence of low birthweight and attribute this finding to improved maternal nutrition during pregnancy.

Documenting the impact of CCTs for pregnant women on abortion decisions is difficult. The practice of abortion is illegal in most Latin American countries unless the life of the mother is at risk. Even in countries in which its practice is legal, there is a substantial stigma attached to it. Hence, there is a natural barrier to collecting data on the practice of abortion, and even more to evaluating the impact of maternity CCTs on abortion decisions. We circumvent this difficulty by using unique internal hospital records from a region with high-abortion rates located in Argentina, near the border with Bolivia. The hospital keeps track of past abortions to better predict the risk level of the current pregnancy, but of course does not report this information to the central government. Data on current abortions are gathered either from abortion cases with complications which ended up at the hospital, or by subsequent follow-ups to pregnant women who showed up at the hospital al least once but did not come back for further checkups.

Participation in the Argentinean CCT for pregnant women is endogenous, which adds another difficulty for its impact evaluation. Eligible women choose whether they want to participate in the program. We use the substantial inflation in Argentina to instrument for this endogenous participation decision. Even though the monthly amount has been adjusted at irregular time intervals to shield the purchasing power of the transfer against inflation, between any two adjustment dates there was a steep loss in purchasing power. We use these differences in purchasing power to essentially define *good* and *bad* months to get pregnant. We believe this IV strategy is of general interest and could be applied to identify causal effects of many other CCTs.

The remainder of this chapter is organized as follows. Section 4.2 provides institutional information about the program. Section 4.3 describes the data and Section 4.4 discusses the proposed econometric strategy. Section 4.5 presents the main results and offer robustness analyses. The last section concludes.

4.2 The AUE Program

Asignación por Embarazo para Protección Social (AUE) is a national program launched in Argentina in May 2011 (decree 446/11) that provides monthly cash transfers to pregnant women who are unemployed, informal (unregistered) workers, registered domestic workers, or so-called social single taxpayers with income below the minimum wage. The main objective of the program is to reduce maternal, perinatal, neonatal, and infant mortality rates that are associated with problems in access to timely health services. Historically, prenatal and maternity benefits to pregnant women in Argentina were linked to employment in the formal sector, which excluded a large segment of unregistered workers and unemployed women. The AUE program was designed to fill this gap. In 2015, the coverage was extended to include small business owners and self-employed pregnant women with a salary below the minimum wage.

4.2.1 Program Eligibility

To be eligible for the program, a woman must be (1) at least 12-weeks pregnant, (2) Argentinian citizen (by birth or option) with a valid id, (3) unemployed, working in the informal sector, or registered as a domestic worker (or as a small taxpayer starting in 2015) with income below the minimum wage,[1] and (4) enrolled in the public health federal program *SUMAR* (only for unemployed women and informal workers).[2] Unemployed women and informal workers with health insurance coverage (privately purchased or employer-sponsored coverage for family members) are excluded from the program. Recipients of the subsidy for women with at least 7 children born alive are also excluded from this program.

[1]The eligibility condition of income below the minimum wage is difficult to verify for informal workers, rendering it inconsequential in practice.

[2]Enrollment into the public health program *SUMAR* can be done in the local health center or hospital. The program *SUMAR* supersedes the AUE program in the sense that all Argentinian women under 64 and children under 19 without health insurance coverage are eligible for enrollment into the *SUMAR* program. The program *SUMAR*, known as *Nacer* before August 2012, dates back to 2004.

4.2.2 Program Components

By May 2011, the monthly transfer was set at AR$ 220, equivalent to US$ 54, 12% of the Argentinean minimum wage, or 1.15 times the basic food basket per adult between 30 and 59 years old.[3] The monthly amount has been adjusted at irregular time intervals to shield the purchasing power of the transfer against inflation. The nominal monthly transfer has increased by more than 20% each year, though Figure 4.1 reveals that its purchasing power has had steep ups and downs.[4]

The transfer has three components. Eighty percent of the monthly transfer is paid monthly between gestational weeks 12 and 42, up to a maximum of 6 months.[5] This first component is paid conditional on meeting the eligibility criteria described above and submitting an application form with the physician signature that certifies the pregnancy condition. The second component involves the remaining 20 percent, which is paid as a lump sum upon delivery or pregnancy interruption. In order to receive the final sum, participants must undergo at least five prenatal checkups with intervals of at least 1 month, two ultrasounds, blood and urine analysis, and receive vaccinations and information on care during the pregnancy. The last program component, launched in December 2019, is an electronic food card, whose monthly value was originally set at AR$ 4,000, equivalent to US$ 63.

As mentioned before, one of the criteria to receive all components of the AUE is the enrollment in the public health program *SUMAR*. Given the design of the plan *SUMAR*, AUE takers who are new enrollees to the *SUMAR* program provide additional financing for their local public health centers, which could potentially increase the quantity and/or quality of health services supplied. With the launch of the AUE in May 2011, 33,125 pregnant women enrolled into the *SUMAR* program, which represents a 30% monthly increase relative to the monthly average of around 25,000 new enrollees during the first quarter of 2011 (January to April).

4.2.3 Program participants

Program take-up increased gradually during its first year, from 5,170 beneficiaries in May 2011 to 68,580 beneficiaries in Dec 2011. Out of the December 2011 recipients, 95.4% were unemployed or working in the informal sector, 3.2% were social single taxpayers, and 1.4% were

[3] In May 2011, the Argentinean minimum wage was AR$ 1840, equivalent to US$ 460. For the same period, the basic food and total baskets were AR$ 192 and AR$ 423 per adult 30-59 years old, respectively.

[4] Given the discrepancies regarding the accuracy of the official CPI index, we follow the literature and use the CPI index of the Province of San Luis.

[5] For pregnancies starting in 2021, the government increased the maximum number of months to 9, equalizing it with the prenatal transfer for formal workers (Law 27,611).

registered domestic workers. According to the latest available statistics, the AUE program benefited 75,476 pregnant women in 2021 (on average across calendar months), which represents roughly 14% of all live births of the country in 2021.[6] Table 4.1 shows the number of women participating in the AUE program, classified by age group. In December 2021, pregnant women between 20 and 29 years old accounted for most of the recipients, representing 60% of the total beneficiaries with known age. To have an idea of how the coverage of the AUE program compares to its counterpart for formal pregnant women, in December 2021 there were 82,046 recipients of the former versus 25,903 recipients for the latter. Ten years after its introduction, the AUE program has benefited almost 2 million pregnant women in Argentina.[7]

Table 4.1: Total number of AUE participants in the country, by period and age group

	Total number of AUE participants in the country						
Period/Age group	15-19	20-24	25-29	30-34	35-39	40+	**Total**
Jun-13	12,667	19,564	12,523	8,005	3,910	1,077	**57,746**
Jun-14	13,593	22,153	13,861	8,521	4,172	1,074	**63,374**
Jun-15	15,840	27,567	17,220	10,268	5,484	1,458	**77,837**
Jun-16	14,658	26,239	17,478	10,151	5,444	1,407	**75,377**
Jun-17	14,476	26,931	18,541	10,578	5,834	1,619	**77,979**
Dec-21	9,426	26,017	23,390	13,897	6,830	2,336	**81,896**

Note: AUE participants with unknown age are excluded. Source: ANSES.

4.3 Data

Several sources of data were combined to make this study feasible. The primary data source for this research are the records of the *Pregnancy Control Program* (PCP) from a public hospital located in the northwest region of Argentina, near the border with Bolivia. Since early 2008, the hospital has maintained health records for all pregnant women who attended the hospital at least once during their pregnancy. At the time of each visit, sociodemographic information of each pregnant women, as well as data related to their particular health conditions, are recorded. For those women who delivered at this hospital, vital statistics completed by physicians at the time of birth are available, containing information on birthweight and sex. The data also

[6] In 2020, vital statistics from the Ministry of Health reported 533,299 live births with a known place of birth. The 14% approximation was found by simply dividing these two figures.

[7] 1,959,565 pregnant women have received at least one monthly AUE transfer between May 2011 and March 2021. Source: ANSES.

contain the unique national identification number (*DNI*) for the pregnant women and allow us to identify the same woman with different pregnancies during the study period.

This hospital is the only public health center in the city, so its records cover the universe of pregnant women from 2008 to 2014. This includes a period before the start of AUE (which took place in May 2011). The treatment variable was not interviewed in the hospital, and therefore it was not available in these records. One advantage of these data is that the hospital receives a considerable number of Bolivian pregnant women since it is located geographically close to that country. Since Bolivian women are not eligible for receiving AUE transfers, their health outcomes can be helpful for estimating the effect of the program.

The control variables that are available in the data include the age of the pregnant mother, the neighborhood where she lives, number of previous children, whether she belongs to a risk group or not, among others. These data also include some information on prenatal care utilization that is collected as the pregnancy progresses. The recorded outcomes of interest are mainly those that refer to the number and timeline of prenatal care visits and health indicators of the newborn babies, such as birthweight.

Finally, individual records from the hospital are matched to social security records from ANSES using the unique *DNI* individual number. These data contain monthly information on formal employment status, health insurance coverage, and all contributory and noncontributory government transfers, including pensions, unemployment benefits, and social assistance benefits of the pregnant woman. From this information we created two key variables: eligibility and treatment status. The treatment variable is a dummy that takes the value 1 if the pregnant woman has received the transfer at least one month during pregnancy, and 0 otherwise. One particular advantage of these new data is that eligibility condition can be established from observed covariates, as opposed to several studies that can only identify treatment but not eligibility status.

As mentioned earlier, 80% of each monthly transfer is paid to all enrolled pregnant women, while the remaining 20% of each monthly transfer is paid after submission of birth certificate and only for those beneficiaries who comply with the required prenatal check-ups during the pregnancy. Since we do not have information on whether each enrolled pregnant woman received the remaining 20%, the treatment variable is defined as *receiving at least the 80% of the AUE monthly transfer in at least one month during pregnancy*.

Two key variables in the data are the records of whether the current pregnancy ended up in an abortion and whether (and how many) abortions in the past has the pregnant woman experienced. To provide context, the National Congress passed the *Voluntary Interruption of*

Pregnancy bill in Argentina in December 2020, which entered into force on 24 January 2021 (Law 27,610). According to the new law, any woman can request the procedure at any public or private health facility in the first 14 weeks of gestation. Prior to 2021, a 1921 law regulated access to and penalties for abortions. According to the old law, abortion could be performed legally by a certified doctor only when the pregnant person's life was at risk or when the pregnancy was a result of rape. Since abortion was mostly illegal during our sample period (2008 to 2014), it is hard to find official reports. However, the hospital maintained internal records of current and past abortions as an input for assessing the risk level of the current pregnancy and maximizing the health outcomes of the mother and the baby.

The data are summarized in Table 4.2. The top panel reports averages for the period January 2008 to April 2011 before the start of the program (pre-program period), while the bottom panel reports information for May 2011 to December 2014 (program period). We report outcomes for three groups of mothers based on their country of origin: those who were born in Argentina, those who were born in Bolivia, and those who were undocumented. Regarding the proportion of current abortions, the data show a clear increase in recorded abortions from the pre-program period to the program period for all groups of mothers. This is consistent with the data quality improvement observed year by year reflected in all variables. Conversations with the hospital manager reveal that there has been periodic employee training and updating of the data spreadsheet from the beginning of the PCP program to better monitor the interactions of the mothers with the health care system. As a consequence, there is an organic increase in several variables across time (e.g., higher prenatal care visits recorded, more complete description of the risk causes). Despite this organic trend, the data show a differential increase in current abortion for Argentinean versus Bolivian women. Argentinean mothers had a 1.3% probability of abortion before the program compared to a 4.6% probability after the program, an increase of 3.3 percentage points. However, the probability of abortion for Bolivian mothers increased 5.6 percentage points over the same period.

The fraction of births below 2,500 grams increased slightly between pre- and program periods, but it was always between 3% and 4%, and Argentinean and Bolivian mothers look similar in this regard. The birthweight measure reinforces this finding by also showing very similar average birthweights around 3,400 grams for all groups of mothers and periods. Argentinean mothers are 3 years younger than Bolivian mothers on average and the same gap can be noticed before and after the introduction of the AUE program. This is also consistent with Argentinean mothers having a higher probability of teen pregnancy, though the gap between Argentinean and Bolivian mothers decreased across time. Argentinean mothers had a 23% and 26% probability of teen pregnancy in the pre-program and program periods, respectively,

an increase of 3 percentage points, while their counterpart for Bolivian mothers was 10% and 18%, respectively, an increase of 8 percentage points.

Table 4.2: Descriptive statistics

	Argentinean	Bolivian	Undocumented
Panel A. Pre-program period (January 2008-April 2011)			
1. Current abortion	.0129	.0091	.0098
2. Past abortion, at least one	.0380	.0818	.0343
3. Birthweight (grams)	3,411	3,480	3,443
4. Low birthweight (<2,500 grams)	.0351	.0303	.0484
5. Mother age	25.19	27.79	26.19
6. Teen pregnancy (<20 years old)	.2294	.1000	.2402
Observations	1,630	110	204
Panel B. Program period (May 2011-December 2014)			
1. Current abortion	.0458	.0647	.0398
2. Past abortion, at least one	.1209	.1223	.0995
3. Birthweight (grams)	3,400	3,462	3,492
4. Low birthweight (<2,500 grams)	.0397	.0366	.0240
5. Mother age	25.02	27.96	25.34
6. Teen pregnancy (<20 years old)	.2635	.1799	.2985
Observations	1,571	139	201

4.4 Econometric Analysis

We begin with a linear model with pregnancy outcome $Y_{i,t}$ for individual i with pregnancy beginning at time t. $Y_{i,t}$ will be either an abortion indicator variable or a measure of birthweight. Our treatment variables of interest are denoted $X_{i,t}$, they will be either an estimate of the value of the cash transfer or an indicator for having received a cash transfer. A vector $W(i,t)$ of conditioning information assumed to be exogenous completes the usual linear model:

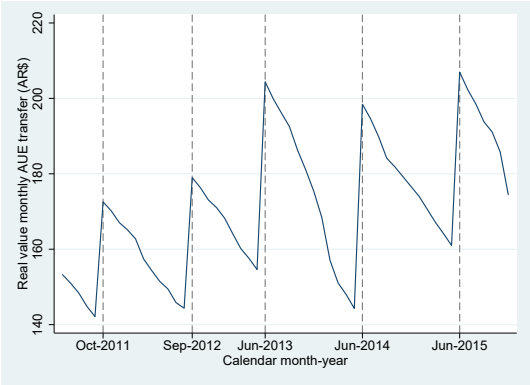
$$Y_{i,t} = a + bX_{i,t} + cW_{i,t} + u_{i,t}. \tag{4.1}$$

We utilize instrumental variables methods to identify b, the treatment parameter of interest. We use two types of instruments, the first $Z1(i,t)$ is simply an indicator variable for Bolivian nationals. Bolivians are not eligible for cash transfer programs from the Argentine government.

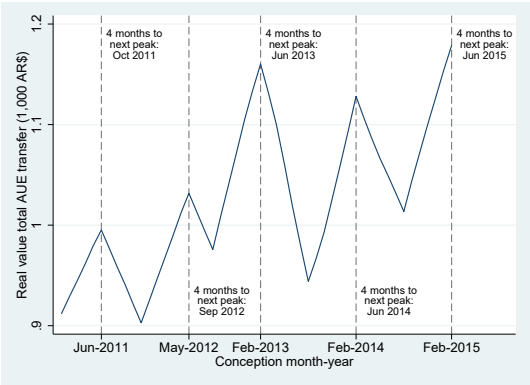
The second type of instrument, denoted $Z2(i,t)$, contains a constructed measure of where time period $falls$ relative to upcoming inflation adjustments. The cash transfer payments we study are occasionally adjusted for the substantial amount of Argentine inflation. This results in considerable variation over time in the real value of transfers, illustrated in Figure 4.1. Women whose pregnancy started 4 months before an inflation adjustment will receive on average 14% more than women whose pregnancy started 6 months later.

Figure 4.1

(a) Real value monthly transfer by calendar month, in AR$ (base 2009)



(b) Real value optimal transfer (sum of 6 months) by conception month, in thousands of AR$ (base 2009)



We employ methods from Conley, Hansen, and Rossi (2012) to investigate relaxations of the exclusion constraint for both of our instruments $Z1$ and $Z2$, collected under Z. Specifically, we modify the outcome equation in our linear model to include these instruments with coefficients that in effect parameterize the degree of violation of their associated exclusion restriction:

$$Y_{i,t} = a + bX_{i,t} + W'_{i,t}c + Z'_{i,t}g + u_{i,t}. \tag{4.2}$$

Our moment condition for estimation is

$$E[W'_{i,t}, Z'_{i,t}]'u_{i,t} = 0. \tag{4.3}$$

The usual exclusion restriction identifying b in model (4.2) is that g is a vector of zeros. We characterize departures from this exclusion restriction by considering non-zero values for g with small violations or "approximate exogeneity" corresponding to small values for g.

With g non-zero and unknown, moment conditions (4.3) are of course under-identified. If g were known to equal g_0, estimation could proceed by simply transforming the outcome variable

to remove the error term correlation with Z:

$$\{Y_{i,t} - Z'_{i,t}g_0\} = a + bX_{i,t} + W'_{i,t}c + u_{i,t}. \tag{4.4}$$

Utilizing $\{Y_{i,t} - Z'_{i,t}g_0\}$ as an outcome variable, b could be estimated via 2SLS using moment condition (4.3). Rather than assume a particular value for g_0 we will conduct inference under assumptions regarding a set of possible values for g.

Specifically, we construct confidence intervals under the assumption that g is in a set B, for a variety assumptions of B. For a given B, we grid up this set and estimate (4.4) via 2SLS and obtain a usual confidence interval for b, for each value of g_0 in this grid. Thus for each value of g_0 we obtain a confidence interval CI(g_0) that is valid under the assumption that the true value of g is g_0. Finally, we take the union of CI(g_0) across all g_0 in the grid for B to obtain an interval estimate of b under the assumption that $g \in B$.

4.5 Empirical Results

Table 4.3 provides IV and OLS estimates of equation (4.1) for the probability of abortion. We find that participation in the program reduces the probability of abortion by 8.8 percentage points. Table 4.4 shows the first stage results. Table 4.5 provides IV and OLS estimates for the incidence of normal birthweight. We find that program participation decreases the incidence of normal birthweight between 6.8 and 7 percentage points.

Table 4.3: Effect of the AUE on the probability of Abortion: program period only

	Abortion indicator			
	IV	OLS	IV	OLS
	(1)	(2)	(3)	(4)
AUE participant	-0.0876**	-0.0474***		
	(0.0432)	(0.0173)		
AUE transfer (1,000 AR$)			-0.0953**	-0.0415**
			(0.0450)	(0.0174)
neighborhood_FE	Yes	Yes	Yes	Yes
pre_program	No	No	No	No
N	673	673	673	673

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4.4: First stage results

	(1) AUE participant	(2) AUE transfer
Bolivian	-0.548***	-0.525***
	(0.0539)	(0.0538)
months to peak ≥ 10	-0.212**	-0.216***
	(0.0825)	(0.0824)
N	673	673
F_stat_excl	60.96	56.74

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In summary, the results show a decrease in the probability of abortion and in the incidence of normal birthweight (i.e., greater than 2,500 grams). This is consistent with a change in composition effect, in which poorer and more disadvantaged women who would have aborted in the absence of the program now decide to continue with their pregnancy but exhibit worse health outcomes. We do not find any impact on gestational length, so the mechanism could be poor maternal nutrition during pregnancy being a key driver of worse birthweight.

4.5.1 Robustness: plausibly exogenous instruments

Figure 4.2 displays results of relaxing the exclusion constraint for both of our instruments $Z1$ and $Z2$ with priors centered at 0. The left panel corresponds to the binary treatment variable, while the right panel shows the results for the continuous treatment variable. The figures plot three sets of confidence intervals indexed by the parameter B_1. The narrowest set of solid lines presents 90% confidence intervals using the union of symmetric g_0-specific intervals with support restrictions of the form $g_{01} \in [-B_1, B_1]$ and $g_{02} = 0$, assuming that $Z2$ is exogenous. The set of dashed lines that lie just outside them correspond to the 90% confidence interval with support restrictions of the form $g_{01} \in [-B_1, B_1]$ and $g_{02} \in [-0.01, 0.01]$. Finally, the set of dotted lines correspond to the 90% confidence interval with support restrictions of the form $g_{01} \in [-B_1, B_1]$ and $g_{02} \in [-0.02, 0.02]$.

Table 4.5: Effect of the AUE on the probability of Birthweight ≥ 2,500 grams: program period only

	Birthweight ≥ 2,500 grams			
	IV	OLS	IV	OLS
	(1)	(2)	(3)	(4)
AUE participant	-0.0711*	-0.0305*		
	(0.0383)	(0.0161)		
AUE transfer (1,000 AR$)			-0.0744*	-0.0312*
			(0.0400)	(0.0163)
neighborhood_FE	Yes	Yes	Yes	Yes
pre_program	No	No	No	No
N	408	408	408	408

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.6 Conclusion

This chapter estimates the causal impact of a maternity conditional cash transfer program in Argentina on the choice between abortion and childbirth in a context where abortion is illegal. We collect data on individual pregnancies and matched them with administrative records regarding women participation in the program. We leverage the substantial amount of inflation in Argentina to instrument for endogenous program participation. We estimate that participation in the program led to a sizable reduction in the incidence of abortion while increasing the probability of low birthweight. Our findings are consistent with a change in composition effect, in which poorer and more disadvantaged women enter the pool of women who decide to have their babies.

Bibliography

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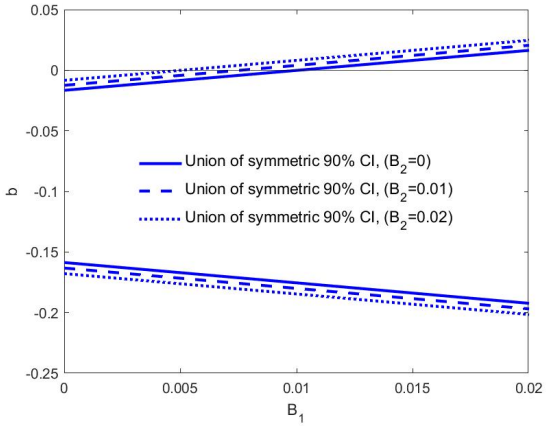
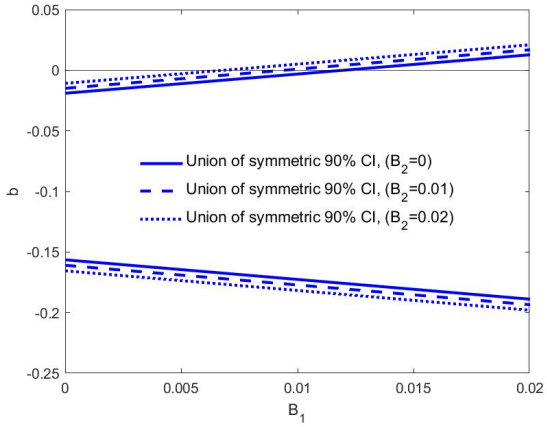
Figure 4.2: Plausibly exogenous instruments

(a) Binary treatment



(b) Continuous treatment



Díaz, J.-J., and V. Saldarriaga (2019): "Encouraging use of prenatal care through conditional cash transfers: Evidence from JUNTOS in Peru," *Health economics*, 28(9), 1099–1113.

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Appendix A

Appendices to Chapter 2

A.1 Experimental enrollment dates by site

The RAND HIE defined a contract year as the 12-month period following each anniversary of the enrollment date. The staggered enrollment dates provide the variation needed to separate the effect of time trends and seasonal demand shocks on the timing of health care utilization decisions.

Table A.1: Enrollment dates

Dayton	Seattle	Massachusetts	South Carolina
11-01-74	01-01-76	07-01-76	11-01-76 (5 yr.)
12-01-74	02-01-76	08-01-76	12-01-76 (5 yr.)
01-01-75	03-01-76	09-01-76	12-31-76 (5 yr.)
02-01-75	04-01-76	10-01-76	01-31-77 (5 yr.)
	05-01-76		11-01-78 (3 yr.)
	06-01-76		12-01-78 (3 yr.)
	07-01-76		01-01-79 (3 yr.)
	08-01-76		02-01-79 (3 yr.)
	09-01-76		

Note: The three-year and five-year groups enrolled at the same times in the locations above, and thus exited two years apart. In South Carolina, the three-year and five-year groups enrolled two years apart and exited at the same time.
Source: Table 4, Codebook 208, Newhouse (1999).

A.2 Beginning- and end-of-experiment effects

Families enrolled in the RAND HIE were informed before they agree to participate that the experiment would end after either 3 or 5 years (randomly assigned before the start of the experiment). This might induce an increase in utilization during the last year of the experiment. Once the experiment is over, enrolled families would most probably return to the insurance plans they had before. Families assigned to full insurance during the experiment would be weakly worse off after the experiment ends, since their experimental plan was probably the most generous plan available in the market. For those enrolled in cost-sharing plans, there is some probability that their before-the-experiment plans were less generous compared to their experimental plan, so they would potentially be worse off once the experiment ends. Similar reasoning applies to the first year of the experiment.

The presence of transitory effects on the demand of health care is not unique to RCTs. Using data from a large self-insured firm, Brot-Goldberg, Chandra, Handel, and Kolstad (2017) find that consumer health care utilization ramps up at the end of the year after which a required plan shift from full insurance to a less generous plan took place. They use the term *anticipatory spending* to describe the extra health care utilization by consumers before the required plan switch actually occurred, when health care was cheaper. In the context of the RAND HIE, the presence of transitory effects has been overlooked until recently. To my knowledge, Lin and Sacks (2019) is the first to document graphically that health care utilization in the RAND HIE free-care plan ramps up over the last months of the experiment. In a concurrent work, Devereux, Balesh Abadi, and Omran (2019) use the term *deadline effect* to describe a spike in health care utilization in the final year of the RAND HIE.

In my context, identifying the presence of beginning- and end-of-experiment effects is important for obtaining a true impact of dynamic moral hazard in health insurance contracts. Without recognizing the presence of an end-of-experiment effect, for example, my estimates of how weekly utilization changes as the end of the contract nears could potentially be positive, contradicting the implication from my model of forward-looking families, on average and ceteris paribus. To uncover the presence of these transitory effects, I introduce first and last contract year fixed effects to the empirical specification of Aron-Dine, Einav, and Finkelstein (2013).

As a baseline, first consider their empirical framework:

$$y_{iq} = \lambda_p + \tau_t + \alpha_{lm} + \epsilon_{iq}, \tag{A.1}$$

which estimates a set of HIE plan p effects given by λ_p on several measures of health care utilization y for individual i in contract year q. Because plan assignment was only random conditional on location and enrollment month, the specification includes a full set of location l by start month m interactions, α_{lm}. Calendar year fixed effects, τ_t, account for any underlying time trend in the cost of health care. Because plans were assigned at the family rather than individual level, all regression results cluster the standard errors on the family.

Now define by $Term_i$ the enrollment term for individual i, with $Term_i \in \{3, 5\}$. I introduce two dummy variables to capture the beginning- and end-of-experiment effects in the first and last contract year, respectively, in the following equation:

$$y_{iq} = \lambda_p + \iota \times \mathbb{1}(q = 1) + \delta \times \mathbb{1}(q = Term_i) + \tau_t + \alpha_{lm} + \epsilon_{iq}, \tag{A.2}$$

where the parameters ι and δ capture the additional health care utilization in the first and last year of the experiment, respectively, compared to middle years. I limit the sample to non-attriters and exclude infants born during the experiment, who enter the experiment as part of the family unit. This ensures a balanced panel. I also exclude the first contract year from Dayton, Ohio, because some health services were treated differently.

Table A.2 reports the results based on estimating equation (A.2) for various measures of health care utilization. In column 1, the dependent variable is the amount of annual health care utilization (in 2011 dollars). I fail to detect any transitory effect in health care utilization when I aggregate all health care categories. This is consistent with some early technical reports by the original RAND investigators. I find that it is necessary to disaggregate utilization by inpatient versus outpatient health care services in order to uncover a significant end-of-experiment effect. Column 3 shows that individuals increase outpatient health care utilization by $203 in their last year of the experiment, relative to middle years, on average. For this reason, I exclude from the estimation sample the last contract year.

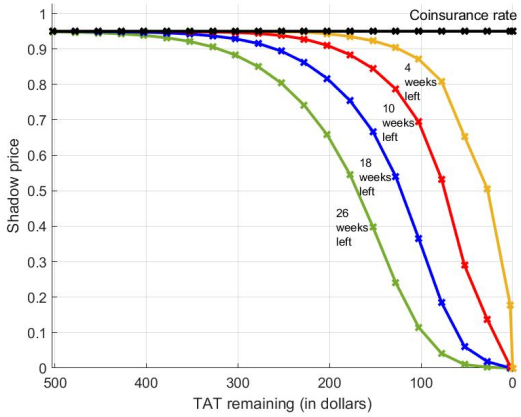
A.3 Model properties of the shadow price of care

A.4 Econometric Details

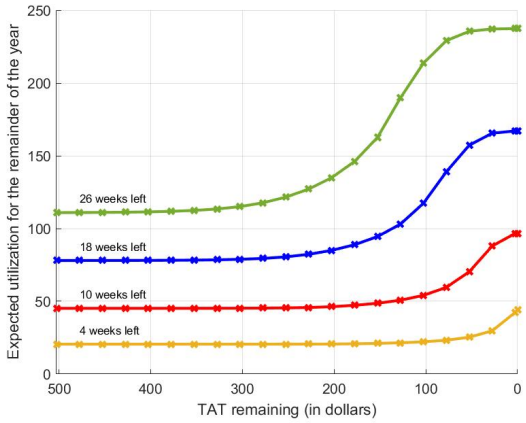
A.4.1 Step 1: Solving the Model

As I describe in Section 2.5 of the main text, in the first step of the estimation algorithm, I solve the dynamic problem for a large number of types, once for each type, and store the

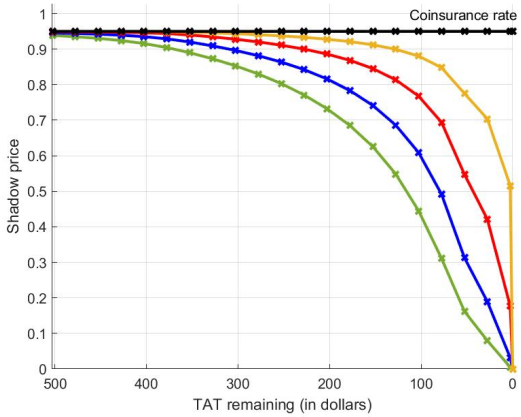
Figure A.1: Model properties of the shadow price of care



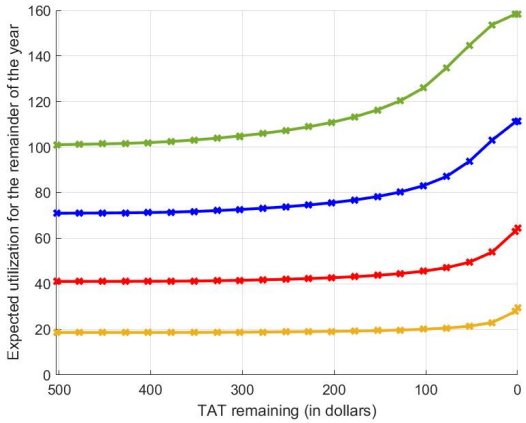
(a) Shadow price, low variance of F_ν, low ω



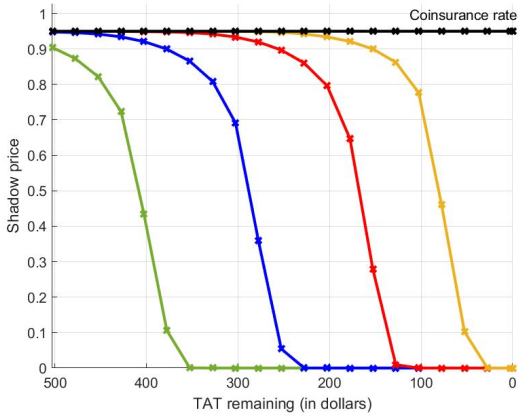
(b) Expected future demand, low variance of F_ν, low ω



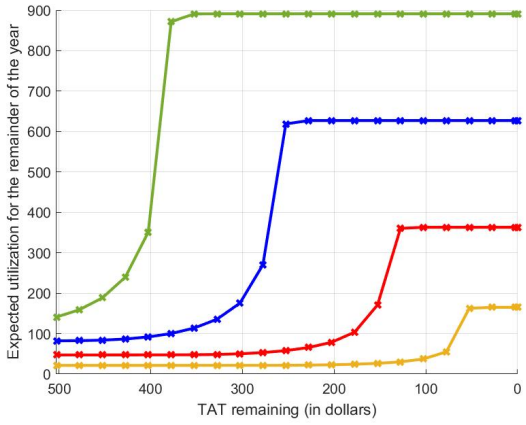
(c) Shadow price, high variance of F_ν



(d) Expected future demand, high variance of F_ν



(e) Shadow price, high ω



(f) Expected future demand, high ω

Table A.2: Beginning- and end-of-experiment effects

	(1) Total utilization in 2011 $	(2) Inpatient utilization in 2011 $	(3) Outpatient utilization in 2011 $
First Contract Year	-71.14	-159.12	87.03
	(150.60)	(127.80)	(69.68)
Last Contract Year	189.70	-13.38	203.27***
	(130.87)	(108.17)	(55.59)
Adjusted R^2	0.011	0.004	0.030
Site x enrol.	Y	Y	Y
Cal. years fe	Y	Y	Y
Family fe	N	N	N
Clustered se	Y	Y	Y
Families	2076	2076	2076
N	12535	12535	12535

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Table A.2 reports selected least-squares coefficients estimates from equation (A.2). Standard errors, clustered on family, are in parentheses below the coefficients. All spending variables are inflation adjusted to 2011 dollars (adjusted using the CPI-U). Site by start month and calendar year dummy variables are demeaned so that the coefficients reflect estimates for the "average" site-month-year mix.

optimal policy.

For a plan, k, and family type, h, I solve the finite-horizon dynamic program recursively. To do so, I discretize the C_t state to a grid of 1,000 points with spacing of size Δc dollars. Time is naturally discrete ($t = 1, 2, \ldots, 52$ over a contract year with $T = 52$ weeks) for my weekly data. These discretizations leave ν_t as the only continuous state variable. Because the family does not know ν_t prior to period t, I can integrate it out and the solution to the dynamic programming problem for each type of family can be characterized by the expected value functions, $E[V_{hkt}(C_{t-1})]$, and policy functions, $E[c^{\star}_{hkt}(C_{t-1})]$. To perform the numerical integration over the bounded support of ν_t, $[0, \overline{\nu}]$, I use adaptive Simpson quadrature.

Having solved the dynamic program for a family of type h, I generate the transition process for the state vector implied by the solution. The transition probabilities between the 52,000 possible states (1000 x 52) are implicitly defined by threshold values for ν_t. For example,

consider a family of type h on plan k, that has consumed C_{t-1} prior to period t. The threshold, $\nu_t(z)$, is defined as the value of ν_t that makes a family indifferent between consuming z units of size Δc dollars and $z+1$ units, such that the marginal utility (net of any out-of-pocket expenditures) of an additional unit of consumption

$$u_h((z+1)\Delta c, y_t, \nu_t(z); k) - u_h(z\Delta c, y_t, \nu_t(z); k)$$

is equated to the loss in the net present value of future utility

$$E[V_{hk(t+1)}(C_{t-1} + (z+1)\Delta c)] - E[V_{hk(t+1)}(C_{t-1} + z\Delta c)].$$

These thresholds, along with all families' initial condition ($C_0 = 0$), define the transition process between states. For each family type h and plan k, I characterize this transition process by the CDF of cumulative health care consumption that it generates,

$$\Gamma_{hkt}(C) = \text{Prob}(C_{t-1} < C),$$

the proportion of families that have consumed less than C through period t of the contract year. Due to the discretized state space, $\Gamma_{hkt}(C)$ is a step function.

A.4.2 Step 2: Estimation

The second step of my estimation approach matches empirical moments I recover from the data to those predicted by my model by choosing weights for each family type.

As I describe in Section 2.5 in the main text, my estimates of the weights are chosen to maximize the objective function. I set the weighting matrix $\hat{V}^{-1}$ equal to the identity matrix.

To recover the cumulative distribution of C_{t-1} for each contract week t and plan k, I use a smooth version of a simple Kaplan-Meier estimator,

$$\widehat{\Gamma}_{kt}(C) = \frac{1}{N_k} \sum_{i=1}^{N_k} \mathbb{1}[C_{i(t-1)} < C],$$

where N_k denotes the number of family-years in plan k and C represents each of the points of the discretized state C_{t-1}. I estimate these moments for each k and t, considering values of C such that $\widehat{\Gamma}_{kt}(C) \in [0, 1]$, ensuring that I fit the tails of the annual health care utilization

distribution.

I recover the moments of health care utilization at each state by estimating a smooth surface using a nearest-neighbor approach. Consider a point in the state space, (C_{t-1}, t). A neighbor is an observation in the data for which the family is t weeks into the contract year and cumulative health care utilization up until contract week t is within five percent of C_{t-1}. Denote the number of neighbors by $N_{kt}(C_{t-1})$. Then, I estimate the conditional (on reaching the state) mean at (C_{t-1}, t) using

$$\widehat{E}[c^{\star}_{kt}(C_{t-1})] = \frac{1}{N_{kt}(C_{t-1})} \sum_{i=1}^{N_{kt}(C_{t-1})} c_i,$$

where $i \in \{1, \ldots, N_{kt}(C_{t-1})\}$ indexes the set of nearest neighbors. If $N_{kt}(C_{t-1}) > 500$, I use those 500 neighbors nearest to C_{t-1}. Note that this gives me the average expenditure conditional on a family arriving at the state. To recover the unconditional mean, I multiply $\widehat{E}[c^{\star}_{kt}(C_{t-1})]$ by the probability of observing a family at state (C_{t-1}, t), recovered from the estimated CDF of cumulative expenditure.

I estimate both moments at the same set of state space points used when numerically solving the dynamic programming problem for each family type. This results in 104,000 moments for each plan of the 10 plans, or 10 x 104,000 = 1,040,000 moments in total.

A.4.3 The choice of moments

Following Nevo, Turner, and Williams (2016), I recover the first set of moments at each state by estimating a smooth surface using a nearest-neighbor approach. Consider a point in the state space, (C_{t-1}, t). A neighbor is an observation in the data for which the family is t weeks into the contract year and cumulative health care consumption up until week t is within five percent of C_{t-1}. Denote the number of neighbors by $NN_{kt}(C_{t-1})$. Then, I estimate the unconditional (on reaching the state) mean at (C_{t-1}, t) using

$$\widehat{m}^{\text{dat}}_{k,1}(C, t) = \frac{\text{Prob}(C_{hk(t-1)} = C, t)}{N(C^{\text{dat}}_{k(t-1)} = C, t)} \sum_{i=1}^{N\left(C^{\text{dat}}_{k(t-1)} = C, t\right)} c^{\text{dat}}_{ikt}.$$

A.4.4 Bootstrap Procedure for Inference

As described in Lahiri (2003), the basic idea behind the bootstrap method is to recreate the relation between the population and the sample using the sample itself. For dependent data, the most common approach to this problem is to resample "blocks" of observations instead of single observations, which preserves the dependence structure of the underlying process *within* the resampled blocks.

My block-bootstrap estimator proceeds with the following repeated procedure:

1. I first draw an alternative dataset sampling with replacement at the family-year level. Specifically, I sample the data by family-year with replacement, keeping all 52 weeks for each family-year drawn. The new dataset has the same number of family-years as the original data.

2. I then use this new dataset to recalculate the proportion of family-years in each plan. These plan weights will be useful for recovering the overall distribution of heterogeneity.

3. For each plan $k = 1, \ldots, 10$ separately, I recalculate the inputs to the moments, $\boldsymbol{m}_k^{\text{dat}}$, and then re-estimate the structural parameters of my model, i.e., the plan-specific weights $\widehat{\boldsymbol{\theta}}_k$.

4. Finally, I calculate the overall type distribution by weighting each $\widehat{\boldsymbol{\theta}}_k$ with the corresponding proportion of family-years in plan k and summing across plans.

For a given type h, the bootstrap confidence interval with $1-\alpha$ coverage can be constructed as

$$CI_{(1-\alpha)\%} = \left[\widehat{\theta}_h - q_h^{\star}\left(1-\frac{\alpha}{2}\right), \widehat{\theta}_h - q_h^{\star}\left(\frac{\alpha}{2}\right)\right], \tag{A.3}$$

where $q_h^{\star}$ is the quantile function of $\widehat{\theta}_h^{\star} - \widehat{\theta}_h$.

I report results from 1,000 bootstrap draws.

A.5 Details about the construction of the grid of family types

I use the *method of good lattice points* to generate a finite collection of points in the five-dimensional space of type heterogeneity. This method was proposed by Korobov (1959) for numerical evaluation of multivariate integrals. The basic idea of a quasi-Monte Carlo method is to replace random samples in a Monte Carlo method by well-chosen deterministic points.

The criterion for the choice of deterministic points depends on the numerical problem at hand. For the important problem of numerical integration, the selection criterion is easy to find and leads to the concepts of uniformly distributed sequence and discrepancy. The discrepancy can be viewed as a quantitative measure for the deviation from uniform distribution.

A.5.1 Discrepancy

The concept of *discrepancy* provides a measure of how dispersed a collection of points is. Let $x_j \in I \equiv [0,1]$, $j = 1, \ldots, N$, be a sequence of scalars. If $S \subset I$, define the cardinality of a set X in a set S, card$(S \cap X)$, to be the number of elements of X which are also in S. Following Judd (1998), I define a notion of discrepancy for finite sets.

Definition A.1 *(Niederreiter, 1992) The* ***star discrepancy*** $D_N^\star$ *of the set* $X \equiv \{x_1, x_2, \ldots, x_N\} \subset [0,1]$ *is*

$$D_N^\star(X) = \sup_{0 \le t \le 1} \left| \frac{card([0,t) \cap X)}{N} - t \right|.$$

Note that $0 \le D_N^\star(X) \le 1$ always. This definition allow us to measure the deviations from uniformity of sets. Even though a continuum of intervals is used in the definition, we need only to check open intervals of the form $(0, x_l)$, $1 \le l \le N$. In the one-dimensional case, a simple explicit formula for $D_N^\star(X)$ can be given.

Theorem A.1 *(Niederreiter, 1992) If* $0 \le x_1 \le x_2 \le \cdots \le x_N \le 1$, *then*

$$D_N^\star(X) = \frac{1}{2N} + \max_{1 \le n \le N} \left| x_n - \frac{2n-1}{2N} \right|.$$

Proof. See Theorem 2.6 in Niederreiter (1992).

It follows from the theorem that we always have $D_N^\star(X) \ge 1/(2N)$, and equality holds if $x_n = (2n-1)/(2N)$ for $1 \le n \le N$. This implies that in the one-dimensional case, the minimum of the star discrepancy $D_N^\star(X)$ is $1/(2N)$ and the classical N-panel midpoint rule for the interval $[0,1]$ achieves this bound. Thus, for low-discrepancy sets in the one-dimensional case, quasi-Monte Carlo methods are not so important. Below I consider the concept of star discrepancy in the multidimensional case.

Definition A.2 *(Niederreiter, 1992) The* ***star discrepancy*** $D_N^\star$ *of the set* $X \equiv \{x_1, x_2, \ldots, x_N\} \subset I^d$ *is*

$$D_N^\star(X) = \sup_{0 \le t_1, \ldots, t_d \le 1} \left| \frac{card([0,t_1) \times \cdots \times [0,t_d) \cap X)}{N} - \prod_{j=1}^{d} t_j \right|,$$

where I^d is the closed d-dimensional unit cube.

A small discrepancy says that the set evenly fills up the hypercube I^d. A set of points X consisting of N elements of I^d is called a low-discrepancy set if $D_N^\star(X)$ is small.

A.5.2 The method of good lattice points

The good lattice point method was proposed by Korobov (1959) for numerical evaluation of multivariate integrals. The method of good lattice points begins with an integer N and a vector of good lattice points $g \in \{0, 1, \ldots, N-1\}^d$, forms the finite collection of points

$$x_l = \left\{ \frac{l}{N} g \right\}, \quad l = 1, \ldots, N, \tag{A.4}$$

and computes the quasi-Monte Carlo approximation

$$\int_{I^d} f(x)dx \doteq \frac{1}{N} \sum_{l=1}^{N} f(x_l), \tag{A.5}$$

where the expression $\{z\}$ denotes the *fractional part of* z.[1] The task is to find combinations of N and g such that the approximation in equation (A.5) is good. In other words, we want to minimize the error in the approximation of equation (A.5), which can be written as

$$R = \left| \int_{I^d} f(x)dx - \frac{1}{N} \sum_{l=1}^{N} f(x_l) \right|$$

The value of R is closely related to the star discrepancy $D_N^\star(X)$, if $F(x)$ satisfies certain conditions. The error analysis for quasi-Monte Carlo integration in Niederreiter (1992) has demonstrated that small errors are guaranteed if sets with small star discrepancy are used. From the view point of numerical analysis, we demand not only the star discrepancy of X should be low but also the set of points X should be convenient for computation.

Good choices of N and g are difficult to compute (Judd, 1998). A strategy pursued by Korobov and others is to examine lattice points that are simply generated and evaluate their performance in integrating certain test functions with known integrals. One test function that

[1] The fractional part of z is formally defined by $\{z\} \equiv z - \max\{k \in \mathbb{Z} | k \leq z\}$.

is particularly valuable is

$$F(x) = \prod_{j=1}^{d} \left(1 - \frac{\pi^2}{6} + \frac{\pi^2}{2}(1 - 2\{x_j\})^2\right),$$

which is defined on I^d and integrate to 1. Note that F is the function in the class of functions having Fourier series in I^d whose Fourier coefficients converge at the slowest possible rate. Korobov (1959) proposes an algorithm for finding lattice points by minimizing R for the function $F(x)$. Keast (1973) extends this algorithm and proves that the lattice points obtained are optimal in Korobov's sense. He first chooses J distinct primes, p_j, $j = 1, \ldots, J$, and lets their product p be the sample size N in equation (A.4). He then chooses a sequence of integers a_j, $j = 1, \ldots, J$. First, a_1 is chosen to minimize

$$H_1(a) \equiv \frac{3^d}{p_1} \sum_{k=1}^{p_1} \prod_{j=1}^{d} \left(1 - 2\left\{k\frac{a^{j-1}}{p}\right\}\right)^2$$

over $a \in \{1, \ldots, p_1 - 1\}$. More generally, for $l = 1, \ldots, J$, a_l minimizes

$$H_l(a) \equiv \frac{3^d}{p_1 \ldots p_l} \sum_{k=1}^{p_1 \ldots p_l} \prod_{j=1}^{d} \left(1 - 2\left\{k\left(\frac{a_1^{j-1}}{p_1} + \cdots + \frac{a_{l-1}^{j-1}}{p_{l-1}} + \frac{a^{j-1}}{p}\right)\right\}\right)^2$$

for $a \in \{1, \ldots, p_l - 1\}$. The *Keast good lattice point* g is then defined to be

$$g_j = \sum_{l=1}^{J} \frac{p}{p_l} a_l^{j-1}, \quad j = 1, \ldots, d.$$

As pointed out in Judd (1998), there is no assurance that the approximations are monotonically better as we increase p, the number of points. Therefore, in constructing a sequence of lattice formulas, one should keep only those formulas that do better in integrating $F(x)$ than formulas with fewer points. $H_J(g)$ serves as a performance index to rank various lattice point rules. Fortunately, there exist tables of good lattice points, g, for specific sample sizes N and dimensions d. The good lattice points have the form $g^d = (1, g_2^d, \ldots, g_d^d) \in \mathbb{R}^d$.[2]

[2]See e.g., Table 9.4 in Judd (1998), Tables 1 and 2 in Bourdeau and Pitre (1985), and Hua and Wang (2012).

A.5.3 Implementation

I use the method of good lattice points to generate a finite collection of points in the five-dimensional space of type heterogeneity. Following Table 9.4 in Judd (1998) which was made according to Keast's method, I fix $N = 1,069$ and $d = 5$, and find the vector of good lattice points $g = (1, 63, 762, 970, 177)$. Using equation (A.4), I then construct the grid of 1,069 points within the $[0, 1)$ hypercube of dimension five. The last step is to redefine the bounds of the $[0, 1)$ hypercube to capture the support of each dimension of heterogeneity.

A.6 *glp* method versus *tpp* method: Monte Carlo Evidence

Up until now I have only highlighted one of the main advantages of the *glp* method: better coverage of the parameter space. However, there is another benefit of using *glp* versus *tpp*: computational efficiency. Next, I perform a small Monte Carlo exercise to illustrate the gains in computational time, without any loss in precision. To do that, I compare the performance of the *good-lattice-points* grid versus the *tensor-product-points* grid within the context of this paper. I fix the number of family-years to 300, and use $M = 100$ replications. I generate data using two alternative distributions $F(\boldsymbol{\beta})$ for the random coefficients. In the first design, the true distribution has the first three characteristics (i.e., μ, σ and κ) heterogeneous across types but correlated within type, and the remaining two components of the type-space are homogeneous across all types. In the second design, all five characteristics of the true distribution are heterogeneous across types and uncorrelated within type. In both designs the underlying true CDF has continuous support.

I use health care consumption data at the family-week-year level, where the true data generating process is the dynamic stochastic model in Section 2.4. For each fake data set, I compute the moments in Section 2.5.2 and estimate a type distribution $\widehat{F}(\boldsymbol{\beta})$ by matching the moments I recover from the data to the weighted average of the behavior predicted by the model. For each run, after I compute the estimate $\widehat{F}(\boldsymbol{\beta})$, I evaluate its squared difference from the true distribution function $F_0(\boldsymbol{\beta})$ at $S = 10,000$ points uniformly spaced. I use root mean integrated squared error (RMISE) to assess performance of both estimators. My definition of RMISE for an estimator $\widehat{F}$ is

$$\sqrt{\frac{1}{M}\sum_{m=1}^{M}\left[\frac{1}{S}\sum_{s=1}^{S}\left(\widehat{F}_m(\boldsymbol{\beta}_s) - F_0(\boldsymbol{\beta}_s)\right)^2\right]}, \tag{A.6}$$

where I use $M = 100$ replications, each with a new fake data set. I also report the integrated

absolute error (IAE), which for a given replication m is

$$\frac{1}{S}\sum_{s=1}^{S}\left|\widehat{F}_m(\boldsymbol{\beta}_s) - F_0(\boldsymbol{\beta}_s)\right|. \tag{A.7}$$

This is a measure of the mean absolute value of the estimation error, taken across the points of evaluation for a given replication. I compute the mean, minimum, and maximum IAE's across the M replications.

The results are given in Table A.3. The first column reports the sample size N, which refers to the number of family-years used for the simulation. The second column describes the method used to populate the grid of types. Whenever the *tpp* method is used, column 2 also provides details about how many points in each dimension were used. The third column reports the number H of types (or basis points) used in the estimation. The next column reports the RMISE of the estimated distribution functions. The following three columns report the mean, minimum, and maximum of the IAE. The final three columns report the mean, minimum, and maximum of the number of types that have positive weight.[3]

While performance of the *tpp* method generally increases with the number of types, it is worth noting that the fit can decrease with increases in H, as the *tpp* grids do not necessarily nest each other for marginal increases in H. In the case where one *tpp* grid is nested inside another one, the RMISE measure should decrease with the number of types R. One example of this can be noted in the first design (i.e., 3D correlated), where the *tpp* grid with 5 points per dimension is nested inside the *tpp* grid with 9 points per dimension.

In the context of correlated random coefficients, the *glp* method provides more flexibility to pick the grid points, as opposed to the *tpp* method. This appealing feature should help in capturing the true underlying distribution more accurately. The results in Panel A of Table A.3 suggest that the *glp* grid exhibits much better performance than the *tpp* grid, even with 10 times less points in the grid. By and large, RMISE and IAE are lower in the *glp* design than in the *tpp* designs. The RMISE of the *glp* grid with 101 points is 0.1066, while the RMISE of the *tpp* grid with 1000 points is 22 percent higher. With only 42.8 grid points with positive mass (on average), the *glp* grid does an excellent job compared to the 170.87 grid points with positive mass (on average) of the *tpp* grid with 10 points per dimension.

[3] A type is considered to have a positive weight if the estimated weight is greater than or equal to 0.01 percent.

Table A.3: Monte Carlo results: 3D correlated and 5D uncorrelated

				Integrated Absolute Error			No. of Positive Weights		
N	Method	R	RMISE	Mean	Min	Max	Mean	Min	Max
				Panel A: 3D correlated					
	glp	101	0.1066	0.0538	0.0354	0.0681	42.80	33	53
	tpp	5^3 =125	0.1414	0.0723	0.0586	0.0877	47.11	17	66
	tpp	6^3 =216	0.1292	0.0657	0.0487	0.0868	71.90	21	98
	tpp	7^3 =343	0.1277	0.0655	0.0427	0.0880	89.22	18	147
	tpp	8^3 =512	0.1347	0.0694	0.0409	0.0888	121.83	21	208
	tpp	9^3 =729	0.1338	0.0676	0.0427	0.0954	135.91	21	276
	tpp	10^3 =1000	0.1299	0.0661	0.0441	0.0948	170.87	20	352
	tpp	11^3 =1331	0.1301	0.0655	0.0416	0.0950	203.20	20	455
	tpp	12^3 =1728	0.1303	0.0661	0.0421	0.0910	240.53	21	582
	tpp	13^3 =2197	0.1307	0.0652	0.0423	0.0937	283.48	21	729
300	tpp	14^3 =2744	0.1311	0.0653	0.0469	0.0899	309.30	19	649
	tpp	15^3 =3375	0.1264	0.0635	0.0385	0.0939	409.96	21	785
	tpp	16^3 =4096	0.1253	0.0638	0.0461	0.0895	454.66	21	849
	tpp	17^3 =4913	0.1236	0.0629	0.0433	0.0901	560.74	23	1093
	tpp	18^3 =5832	0.1164	0.0587	0.0393	0.0890	601.30	22	1264
	tpp	19^3 =6859	0.1225	0.0628	0.0383	0.0896	725.76	18	1496
	tpp	20^3 =8000	0.1186	0.0605	0.0439	0.0884	871.84	26	1765
	tpp	21^3 =9261	0.1201	0.0611	0.0400	0.0897	898.19	23	1855
	tpp	22^3 =10648	0.1193	0.0607	0.0400	0.0898	1001.6	21	2246
	tpp	23^3 =12167	0.1260	0.0640	0.0422	0.0916	1101.8	25	2434
	tpp	24^3 =13824	0.1206	0.0621	0.0439	0.0867	1031.1	25	2670
				Panel B: 5D uncorrelated					
	glp	1069	0.0866	0.0400	0.0285	0.0651	119.77	16	323
300	tpp	5^5 =3125	0.0919	0.0484	0.0351	0.0877	329.74	35	567
	tpp	6^5 =7776	0.0849	0.0442	0.0273	0.0761	715.57	41	1227
	tpp	7^5 =16807	0.0873	0.0462	0.0313	0.0915	1143.70	69	2472

A.7 Decomposition of Relative Social Surplus

The certainty equivalent to a contract j at premium $premium_j$ for a type-h family with initial income Y is given by $e_{hj}(\boldsymbol{\beta}_h)$, as defined in equation (2.21) and repeated here:

$$e_{hj}(\boldsymbol{\beta}_h) \equiv -\frac{1}{\psi} \ln\left[\int \exp(-\psi\, \tilde{u}^{\star}(\boldsymbol{\nu}, \boldsymbol{\beta}_h, j)) dF_{\boldsymbol{\nu}}(\boldsymbol{\nu})\right] + (Y - premium_j).$$

The certainty equivalent can also be expressed as

$$\begin{aligned} e_{hj}(\boldsymbol{\beta}_h) &= EV(j,h) - \frac{1}{\psi}\ln\left[\int \exp(-\psi\,\tilde{u}^{\star}(\boldsymbol{\nu},\boldsymbol{\beta}_h,j))dF_{\boldsymbol{\nu}}(\boldsymbol{\nu})\right] + (Y - premium_j) - EV(j,h) \\ &= EV(j,h) + Y - premium_j - RP(j,h), \end{aligned}$$

where $EV(j,h) + Y - premium_j$ is the expected payoff and $RP(j,h)$ is the risk premium associated with the lottery. In particular,

$$\begin{aligned} EV(j,h) &= \mathbb{E}_{\boldsymbol{\nu}}\left[\sum_{t=1}^{T_j}((c_t^{\star} - \nu_t) - \frac{1}{2\,\omega}(c_t^{\star} - \nu_t)^2 - \mathcal{O}(c_t^{\star}, C_{t-1}; j))\right], \quad \text{and} \\ RP(j,h) &= EV(j,h) + \frac{1}{\psi}\ln\left[\int \exp(-\psi\,\tilde{u}^{\star}(\boldsymbol{\nu},\boldsymbol{\beta}_h,j))dF_{\boldsymbol{\nu}}(\boldsymbol{\nu})\right] \end{aligned} \tag{A.8}$$

The corresponding insurance provider's welfare for a type-h family enrolled in contract j is given by his expected profits, as defined in equation (2.22) and repeated here:

$$\pi_{hj}(\boldsymbol{\beta}_h) \equiv premium_j - \mathbb{E}_{\boldsymbol{\nu}}\Big[k_j(C^{\star}_{T_j}(\boldsymbol{\nu},\boldsymbol{\beta}_h,j))\Big],$$

where $k_j(.)$ is the function that maps family's total health care utilization to the portion covered by the provider under the price scheme of contract j.

The social surplus generated by allocating a type-h family to contract j is given by

$$SS_{hj}(\boldsymbol{\beta}_h) = e_{hj}(\boldsymbol{\beta}_h) + \pi_{hj}(\boldsymbol{\beta}_h)$$

Finally, the *relative* social surplus generated by allocating a type-h family to contract j (relative to allocating the same family to the free-care contract) is given by RSS_{hj}, as defined in equation (2.23) and repeated here:

$$RSS_{hj}(\boldsymbol{\beta}_h) \equiv SS_{hj}(\boldsymbol{\beta}_h) - SS_{h,\text{free}}(\boldsymbol{\beta}_h)$$

The relative social surplus can also be expressed as

$$
\begin{aligned}
RSS_{hj}(\boldsymbol{\beta}_h) &= \tilde{e}_{hj}(\boldsymbol{\beta}_h) - \tilde{e}_{h,\text{free}}(\boldsymbol{\beta}_h) - \mathbb{E}_{\boldsymbol{\nu}}[k_j(C^{\star}_{T_j}(\boldsymbol{\nu},\boldsymbol{\beta}_h, j)) - C^{\star}_{T_j}(\boldsymbol{\nu},\boldsymbol{\beta}_h, \text{free})] \\
&= [EV(j,h) - RP(j,h)] - [EV(\text{free},h) - RP(\text{free},h)] - \mathbb{E}_{\boldsymbol{\nu}}[k_j(C^{\star}_{T_j}(\boldsymbol{\nu},\boldsymbol{\beta}_h, j)) - C^{\star}_{T_j}(\boldsymbol{\nu},\boldsymbol{\beta}_h, \text{free})] \ldots \\
&\quad + [EV^{\text{myopic}}(j,h) - \mathbb{E}_{\boldsymbol{\nu}}[k_j(C^{\star,\text{myopic}}_{T_j}(\boldsymbol{\nu},\boldsymbol{\beta}_h, j))] \ldots \\
&\quad - [EV^{\text{myopic}}(j,h) - \mathbb{E}_{\boldsymbol{\nu}}[k_j(C^{\star,\text{myopic}}_{T_j}(\boldsymbol{\nu},\boldsymbol{\beta}_h, j))]] \\
&= \underbrace{\Psi(j,h)}_{\substack{\text{Relative value of} \\ \text{risk protection}}} - \Big[\underbrace{\Sigma(j,h)}_{\substack{\text{Relative social cost of} \\ \text{static moral hazard}}} + \underbrace{\Delta(j,h)}_{\substack{\text{Relative social cost of} \\ \text{dynamic moral hazard}}} \Big],
\end{aligned}
$$

where

$$
\begin{aligned}
\Psi(j,h) &= RP(\text{free},h) - RP(j,h) && \leq 0, \\
\Sigma(j,h) &= [-EV^{\text{myopic}}(j,h) + \mathbb{E}_{\boldsymbol{\nu}}[k_j(C^{\star,\text{myopic}}_{T_j}(\boldsymbol{\nu},\boldsymbol{\beta}_h, j))]] + [EV(\text{free},h) - \mathbb{E}_{\boldsymbol{\nu}}[C^{\star}_{T_j}(\boldsymbol{\nu},\boldsymbol{\beta}_h, \text{free})]] && \leq 0, \\
\Delta(j,h) &= [-EV(j,h) + \mathbb{E}_{\boldsymbol{\nu}}[k_j(C^{\star}_{T_j}(\boldsymbol{\nu},\boldsymbol{\beta}_h, j))]] + [EV^{\text{myopic}}(j,h) - \mathbb{E}_{\boldsymbol{\nu}}[k_j(C^{\star,\text{myopic}}_{T_j}(\boldsymbol{\nu},\boldsymbol{\beta}_h, j))]] && \geq 0.
\end{aligned}
$$

The (relative) value of risk protection, $\Psi(j,h)$, is non-positive because any contract j provides a weakly riskier distribution of payoffs than the free-care contract.

A.8 Details about the RAND HIE design and the construction of the analysis sample

Approximately 2,500 nonelderly families (or 7,700 individuals) were assigned to one of 14 fee-for-service (FFS) insurance plans or to a prepaid group practice. The fee-for-service plans varied along two principal dimensions: the coinsurance rate (the fraction of billed charges paid by the participant) and the maximum dollar expenditure (MDE), a cap on family out-of-pocket expenditures during a 12-month accounting period. The design used four coinsurance percentages (0, 25, 50, and 95) and three levels of MDE (5, 10, or 15 percent of family income, up to a maximum of $1,000). In one exceptional plan the MDE was set at $150 per person or $450 per family. These various coinsurance and MDE rates were combined as follows:

- **FFS plan 1:** one plan with zero coinsurance (free care).
- **FFS plans 2 to 4:** three plans with 25 percent coinsurance and MDEs of 5, 10, or 15 percent of family income or $1,000, whichever was less.
- **FFS plans 5 to 7:** three plans with 50 percent coinsurance and MDEs of 5, 10, or 15 percent of family income or $1,000, whichever was less.

- **FFS plans 8 to 10:** three plans with 50 percent coinsurance and MDEs of 5, 10, or 15 percent of family income or $1,000, whichever was less.
- **FFS mixed plans 11 to 13:** three plans with 25 percent coinsurance for all services except outpatient mental health and dental, which were subject to 50 percent coinsurance; and MDEs of 5, 10, or 15 percent of family income or $1,000, whichever was less.
- **FFS mixed plan 14:** one plan with 95 percent coinsurance for outpatient services and 0 percent coinsurance (free care) for inpatient services and a MDE of $150 per person, subject to a maximum of $450 per family.
- **Prepaid group practice plan 15:** one plan with 0 percent coinsurance (free care) if care was received at a Seattle Health Maintainance Organization (HMO), Group Health Cooperative of Puget Sound; 95 percent coinsurance if care was received outside the HMO.

I make four restrictions to create my baseline sample.

1. My model does not distinguish between providers of service (e.g., physician versus dentist) or whether the provider belongs to the prepaid group network.
2. Dental and mental health services were treated differently in the first year of the experiment in Dayton, Ohio. Dental services for adults were covered only on the free-care plan (dental services for children were covered on all plans). Outpatient mental services were not covered.
3. For any family-year observation in the free-care plan with missing MDE, I imputed a MDE equal to zero.

The number of families at enrollment does not necessarily coincide with the number of families that completed the experiment, even in the absence of attrition (see Footnote 12). Indeed, absent attrition, the number of families at enrollment is the lower bound for the number of families that completed the experiment.

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Appendix B

Appendices to Chapter 3

B.1 Alternative measure of risk aversion

Table B.1: Mean risk aversion by families' responses to the hypothetical offers

Case	Answers	Families	Formula for ψ	Mean ψ
1	"No" to all non-missing scenarios	148	midpoint in $[0, \overline{\psi}]$	0.0022
2	At least one "Yes" and one "No"	438	midpoint in $[\underline{\psi}, \overline{\psi}]$	0.0062
3	"Yes" to all non-missing scenarios	480	$\underline{\psi}$	0.0122
Total		1,066		0.0084

Table B.2: Regression coefficients of each dimension of unobserved heterogeneity on the indicator variable for absolute risk aversion above the median

	(1) *HealthRisk*	(2) *PrefDoctor*	(3) *MoralHazard*	(4) *Income*
RiskAversion above median	-19.04	-30.54***	50.23***	-5174.67***
	(11.67)	(3.06)	(1.89)	(330.82)
R^2	0.00	0.09	0.42	0.20
Number of families	968	968	968	968

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Options 1 (*Yes, I certainly would*) and 2 (*I probably would*) are classified as "Yes" answers, and therefore determine a lower bound for risk aversion. Options 3 (*I probably would not*) and 4 (*No, I certainly would not*) are classified as "No" answers, and therefore determine an upper bound for risk aversion.

Table B.3: Regression coefficients of each dimension of unobserved heterogeneity on the continuous measure of absolute risk aversion

	(1) *HealthRisk*	(2) *PrefDoctor*	(3) *MoralHazard*	(4) *Income*
RiskAversion	-96.06	-86.59	118.02**	-19153.29**
	(195.63)	(53.75)	(41.48)	(6170.45)
R^2	0.00	0.00	0.01	0.01
Number of families	968	968	968	968

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Options 1 (*Yes, I certainly would*) and 2 (*I probably would*) are classified as "Yes" answers, and therefore determine a lower bound for risk aversion. Options 3 (*I probably would not*) and 4 (*No, I certainly would not*) are classified as "No" answers, and therefore determine an upper bound for risk aversion.

Appendix C

Appendices to Chapter 4

C.1 The AUE Program Form

ANSES

Form. PS.2.67

Solicitud Asignación por Embarazo para Protección Social

USO EXCLUSIVO ANSES

Frente

Código Dependencia	UDAI	Trámite Nº

Solicitud	Acreditación	Aceptada	Rechazada

Rubro 1 - Datos del Titular Declaración Jurada de Datos Consignados

CUIL _____ Nº de Documento _____

Apellido/s y Nombre/s _____

Correo Electrónico _____

Teléfono de Contacto _____

Posee cobertura de Obra Social: Si ☐ No ☐

Si Consigna "SI". Indique Situación: Monotributista Social ☐ Servicio Doméstico ☐ Trabajo de Temporada ☐

Si Consigna "No". Presenta Inscripción al Plan Nacer ☐

Declaro bajo juramento que mi grupo familiar cumple con los requisitos establecidos en el Decreto Nº 1602/09 y sus normas reglamentariaspara el cobro de esta Asignación por Embarazo para Protección Social y no estamos alcanzados por las incompatibilidades del Artículo 9º del mencionado decreto.

Datos del Representante Legal/Natural del Titular Solo cumplimentar en el caso de que el Titular sea Menor de 18 Años

CUIL _____ Nº de Documento _____

Apellido/s y Nombre/s _____

Firma del Titular / Representante o Impresión Dígito Pulgar Derecho

Aclaración de Firma

Rubro 2 - Constancia Médica para la Solicitud de la Asignación por Embarazo para Protección Social

Fecha: _____ Semanas de Gestación (entre 12 y 42 semanas): _____ Fecha Probable de Parto: _____

Matrícula Nº: _____ Nacional ☐ Provincial ☐

Apellido/s y Nombre/s del Profesional: _____

La cumplimentación de este rubro acredita que la Titular se encuentra embarazada.

Lugar _____

Firma y Sello del Profesional Certificante

Rubro 3 - Acreditación de Requisitos Médicos del Embarazo

Indique lo que Corresponda Nacimiento ☐ Interrupción del Embarazo ☐ Fallecimiento ☐ Fecha: _____

Control Integral del Embarazo ☐ (Controles Prenatales, Laboratorio, Ecografías, Inmunizaciones, Consejería)

Matrícula Nº: _____ Nacional ☐ Provincial ☐

Apellido/s y Nombre/s del Profesional: _____

Lugar y Fecha _____, ____/____/_____

Firma y Sello del Profesional Certificante

Presenta la Inscripción al Plan Nacer del recién nacido (Uso exclusivo de ANSES) ☐

Rubro 4 - Recepción (Para Uso Exclusivo de ANSES)

Firma, Aclaración y Legajo del Agente Interviniente

Fecha y Sello de Recepción

Ministerio de Trabajo, Empleo y Seguridad Social

ANSES

Form. PS.2.67

Solicitud Asignación por Embarazo para Protección Social

Constancia de Recepción

Uso Exclusivo ANSES

Solicitud	Acreditación	Aceptada	Rechazada	Trámite Nº

CUIL _____ Nº de Documento _____

Apellido/s y Nombre/s _____

Ministerio de Trabajo, Empleo y Seguridad Social

Firma, Aclaración y Legajo del Agente Interviniente

Fecha y Sello de Recepción

Form. PS2.67 (Dorso)

Instrucciones para la Cumplimentación

Rubro 1 - Datos de la Titular

En este rubro se deberán consignar los datos de la mujer embarazada y si cuenta o no con cobertura de obra social.

En caso de que se consigne que posee cobertura de obra social, sólo podrá solicitar esta Asignación en la medida que su situación sea Monotributo Social, Servicio Doméstico o Trabajo de Temporada.

Documentación a Presentar: (en caso de no poseer cobertura de Obra Social):

- Constancia de Inscripción de la Titular al Plan Nacer (debiendo el operador de ANSES cumplimentar con una tilde el campo correspondiente).

Rubro 2 - Constancia Médica para la Solicitud de la Asignación por Embarazo

En este rubro el profesional certificante deberá cumplimentar los campos y acreditar que la Titular se encuentra embarazada.

El tiempo de gestación consignado por el profesional certificante no podrá ser inferior a 12 semanas ni superior a 42 semanas.

Rubro 3 - Acreditación de Requisitos Médicos del Embarazo

Una vez finalizado el estado de embarazo, en este rubro el profesional certificante deberá consignar si se produjo el nacimiento y/o fallecimiento del niño ó la interrupción del embarazo y la fecha en la que sucedió lo indicado.

El profesional certificante deberá consignar con una tilde que a la titular se le efectuó el Control Integral del Embarazo.

Documentación a Presentar:

En caso de Nacimiento:

- Original y copia de la Partida o del Certificado de Nacimiento
- Constancia de Inscripción del recién nacido al Plan Nacer (debiendo el operador de ANSES cumplimentar con una tilde el campo correspondiente)
- Original y copia del Documento Nacional de Identidad del recién nacido (opcional)

en Caso de Fallecimiento:

- Original y copia del Certificado de Defunción

En caso de Interrupción del Embarazo:

- La cumplimentación de este rubro es requisito suficiente para su acreditación

Rubro 4 - Recepción

El operador de ANSES deberá firmar, fechar y sellar la recepción del formulario.

Información Importante

Profesional Certificante:

En caso de Nacimiento un médico (tocoginécologico, generalista, de familia) y/u obstétrica deberá acreditar el cumplimiento del control integral del embarazo. En caso de Interrupción del Embarazo o Fallecimiento del recién nacido deberá ser acreditado por un profesional médico.

"El Control Integral del Embarazo" debe incluir al menos las siguientes prestaciones:

- Carnet Perinatal: guía que debe utilizar la embarazada para constatar el control y cuidado de su embarazo el que le será entregado por el profesional médico u obstétrico.
- Calendario de controles prenatales completos: 5 controles prenatales con intervalos de al menos 1 mes.
- Consejería integral en salud sexual y en el cuidado de la salud y la de su hijo/a.
- 2 ecografías.
- En el segundo y anteúltimo control prenatal: datos de serología (VDRL, Hepatitis B, HIV, Chagas y Toxoplasmosis) y Hematocrito y Hemoglobina (anemia).

El Esquema de Vacunación en el embarazo incluye:

- Vacuna antigripal: deberá darse a todas las embarazadas en cualquier trimestre de gestación.
- Doble Adulto: de no contar con el esquema completo, o sea, si no se tiene una dosis registrada en los últimos 10 años, se debe dar una dosis.

El Esquema de Vacunación en el puerperio incluye:

- Vacuna antigripal: si no la recibió en el embarazo.
- Doble adulto: de no contar con el esquema completo, o sea, si no se tiene una dosis registrada en los últimos 10 años, se debe dar una dosis.
- Doble Viral o Triple Viral (en el post-parto): si no tiene registro de al menos 2 dosis de la vacuna después del año de edad o una dosis en la última campaña, deberá darse cualquiera de estas vacunas.

El Esquema de Vacunación para el Recién Nacido incluye:

- BCG antes del alta de la maternidad.
- Hepatitis B antes de las 12 horas de vida.

ESTE FORMULARIO REVISTE CARÁCTER DE DECLARACIÓN JURADA, DEBE SER CUMPLIMENTADO EN LETRA IMPRENTA SIN OMITIR, ENMENDAR NI FALSEAR NINGÚN DATO, SUJETANDO A LOS INFRACTORES A LAS PENALIDADES PREVISTAS EN LOS ARTS. 172, 292, 293 Y 298 DEL CÓDIGO PENAL PARA LOS DELITOS DE ESTAFA Y FALSIFICACIÓN DE DOCUMENTO PÚBLICO.

EL PAGO DE LA ASIGNACIÓN POR EMBARAZO PARA PROTECCIÓN SOCIAL SOLICITADA QUEDA CONDICIONADO AL CUMPLIMIENTO DE LOS REQUISITOS ESTABLECIDOS EN LAS NORMAS VIGENTES Y SIEMPRE QUE NO EXCEDAN DE 6 (SEIS) MENSUALIDADES.

ESTE FORMULARIO REVISTE CARÁCTER DE DECLARACIÓN JURADA, DEBE SER CUMPLIMENTADO EN LETRA IMPRENTA SIN OMITIR, ENMENDAR NI FALSEAR NINGÚN DATO, SUJETANDO A LOS INFRACTORES A LAS PENALIDADES PREVISTAS EN LOS ARTS. 172, 292, 293 Y 298 DEL CÓDIGO PENAL PARA LOS DELITOS DE ESTAFA Y FALSIFICACIÓN DE DOCUMENTO PÚBLICO.

EL PAGO DE LA ASIGNACIÓN POR EMBARAZO PARA PROTECCIÓN SOCIAL SOLICITADA QUEDA CONDICIONADO AL CUMPLIMIENTO DE LOS REQUISITOS ESTABLECIDOS EN LAS NORMAS VIGENTES Y SIEMPRE QUE NO EXCEDAN DE 6 (SEIS) MENSUALIDADES.

Curriculum Vitae

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