How Do Couples Choose Individual Insurance Plans? Evidence from Medicare Part D

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Job Market Paper

November 11, 2019

Abstract

This research is the first economic study to investigate how couples make enrollment choices in individual insurance markets. I leverage administrative records for Medicare Part D enrollees to distinguish widows and divorcées from married couples. I estimate a stochastic choice model of household demand that takes into account risk aversion, expenditure risk, risk sharing and inertia. I use the model estimates to study how coordination within couples and interaction between couples and singles affects the way that markets adjust to policies designed to nudge individuals toward choosing higher value plans, particularly with respect to adverse selection. The data reveals striking facts about insurance choice. Strikingly, I find that 78% of couples decide to "pool" by buying the same plan. This figure remains constant even for couples with extremely different health risk. My estimates imply that monetary value of plan pooling to the average couple is approximately half their monetary value of inertia, \$1,584 vs \$3,152. I use the model estimates to conduct several counterfactual policy experiments and find that nudging consumers to choose the plans that maximize their expected utility in a hypothetical deregulated environment without risk adjustment and premium subsidies would increase couples' welfare by 11% and decrease singles' welfare by 2% on average. Adding the federal government's current risk adjustment formula increases the disparity between welfare gains for couples and welfare losses for singles. Additionally adding the federal government's current formula for subsidizing plan premiums causes the policy to generate average welfare gains among both couples and singles of 36% and 5% respectively.

*I am grateful to Nick Kuminoff, Jonathan Ketcham, Eddie Schlee, and Dan Silverman for their guidance and support. I would also like to thank Gustavo Ventura, Domenico Ferraro, Alvin Murphy, Kelly Bishop, Natalia Kovrijnykh, Esteban Aucejo, Santiago Garcia-Couto, Luis Fernandez Intriago, Jorge Mesias Moreno, Nirman Saha, Sophie Mathes, Jacob French, Jakob Dowling and participants at various seminars for helpful comments.

Couples often participate in *individual* health insurance markets, many of which are federally regulated. Examples include Medicare Advantage, Medicare Part D and Medigap. In these markets, married couples have incentives to coordinate their plan choices since they share a budget constraint, risks, and information obtained from their search processes. Virtually nothing is known about this form of coordination and its implications for equity and efficiency of markets. Understanding how couples coordinate their enrollment decisions is potentially important for evaluating consumer welfare from health insurance and for assessing policies targeting market design. For example, if spouses' average cost is similar to singles, then the degree of assortative mating in risk will affect the intensity of adverse selection. Equally important, if couples are less risk averse than their individual members, because they are able to share risks, then their collective enrollment decisions will differ from the plans they would have chosen separately. Marital status may also contain policy relevant information about risk beyond what can be learned from existing medical conditions and demographics.

This research is the first economic study to investigate how couples make enrollment choices in individual insurance markets. I leverage administrative records to determine the marital status of a large panel sample of Medicare Part D enrollees. I first distinguish households that are comprised of married couples from households that consist of singles who are widowed or divorced. Then, for each type of household I estimate a stochastic choice model of insurance demand that incorporates risk aversion, expenditure risk, and inertia. Finally, I combine my estimates for household-level insurance demand with a parsimonious model of plan pricing to study the distributional welfare consequences of policies designed to nudge individuals or households toward choosing certain types of plans. This exercise allows me to investigate how coordinated decision making by couples modifies the implications of nudging for adverse selection. I also use the model to investigate how standard regulations in health insurance markets affect the ways in which singles and couples would sort themselves across the market in response to nudges, and what this sorting behavior implies for consumer welfare.

I start by using information on a random sample of approximately 2 million beneficiaries' residential locations, last names and basis for social security eligibility to identify different household types. These data allow me to identify approximately

75,000 couples making repeated insurance plan choices over the first five years of the Medicare Part D program, 2006-2010. These data enable me to provide the first direct evidence on how couples make their insurance plan enrollment decisions, and how their behavior compares with singles who are widowed or divorced.

The linked household-level data reveal several striking facts about couples' insurance plan choices. First, nearly 80% of couples buy the same plan. Second, this statistic is virtually invariant to the difference between spouses' health risks. Third, inertia affects couples and singles similarly, implying that couples do not fully exploit economies of scale in information. Indeed, approximately 85% of married couples reenroll in their default plan combinations each year. Fourth, while I find some evidence of positive assortative mating in prescription drug risk, the magnitude is small compared to evidence on assortative mating in other contexts such as education, (Fernández, Guner and Knowles, 2005). Fifth, couples account for a substantial share of the market (54%) and, on average, have substantially lower costs for insurance companies ($871) compared to widows, who account for 30% of the market and have average costs of $1,116.[1] Moreover, this difference is exacerbated by the way the federal government adjusts subsidies to insurance companies based on the risk of its consumer pool, which inflates the cost differential between couples and widows by 35%.

I model household behavior with a stochastic choice model. Households are assumed to choose plans based on a deterministic core theory, expected utility, and a random error, (Hey and Orme, 1994; Harless et al., 1994; von Gaudecker, van Soest and Wengstrom, 2011). The scale of the logistic error will be household-type-specific to capture heterogeneity in households' decision processes. I follow standard practice in the health insurance literature by adding "inertia" parameters describing the disutility of switching plans to help explain the low rates of consumer switching. Similarly, I add "pooling" parameters describing the disutility for couples to choose separate plans to help explain the low rates at which couples choose different plans. Each household type will choose plans that maximize the certainty equivalent corresponding to expected utility, plus the combined effects of inertia, pooling, and a random shock. This representation allows me to represent

[1] Costs here represent total prescription drug expenditures minus the out of pocket expenditure of each household. This difference represents the cost that insurance companies incur.

plan choices as lotteries with inertia and pooling defined in certainty equivalent terms, similar to Handel (2013).

Estimation proceeds in two stages. First I estimate a distribution of individual-specific parameters describing the degree of constant absolute risk aversion (CARA) using data from the Health and Retirement Study (HRS). Then I use observable measures of individual demographics and prescription drug spending to project this distribution onto the Medicare Part D population. The risk aversion parameters are identified by individuals' responses to a set of questions in the HRS that were designed to elicit risk aversion by asking each individual to choose among hypothetical monetary gambles. I find that risk aversion tends to be higher among older individuals, those with higher prescription drug expenditures, and females. Then I use the risk aversion measures predicted for each individual in each household to construct a CARA specification for household utility. This implies that widows are the most risk averse household types, and married couples the least.

Next I estimate household utility parameters for each household type. The monetary value of pooling ($1,584) is approximately half the implied monetary estimates of status quo inertia for couples, ($3,152). This is striking, given that both behaviors likely reflect some of the same mechanisms. Status quo inertia for widows is $1,975 compared to $1,472 for divorced women. Inertia is higher among widows because they are the most risk averse agents in the market and stand to gain the most by switching. The fact that they switch at the same rate as less risk averse household types is rationalized by higher inertia. I demonstrate that the difference in inertia between couples and singles is consistent with the hypothesis that one spouse selects both plans.

I use my estimates to simulate a counterfactual policy experiment in which a regulator nudges consumers to conform with expected utility. The experiment is replicated in environments with and without premiums subsidies and risk adjustment payments. Importantly, I recognize that the policy may affect couples and singles differently. In the actual Part D setting, both household types are made better off by the policy. Even a policy that only succeeds in altering households' decision processes is able to generate welfare increases of up to a 24% for couples and 18% for singles. Premiums decrease on average, revealing that most plans get advantageously selected. To better understand the mechanisms driving these results and explore model predictions in less regulated environments I replicate the same policy after eliminating premium subsidies. This alteration reduces the size of couples' welfare gains from the nudge, whereas singles are made worse off by the policy. Their welfare decreases by 8% on average. The nudge tends to induce (relatively low cost) couples to reduce their expenditures on plan premiums by moving to plans with smaller shares of widows. The subsequent increase in premiums makes (relatively high cost) singles who remain in those plans worse off. When I further eliminate risk adjustment I find that nudging enrollees increases couples' welfare and decreases singles' welfare moderately. The decrease among singles' is smaller relative to the environment with risk adjustment because risk adjustment makes singles more costly relative to couples. When couples sort into plans with smaller shares of widows, the variation in premiums is smaller relative to the environment with risk adjusted payments. Overall, these policy experiments reveal that premium subsidies are the key institutional feature that make the policy welfare-enhancing for most enrollees. This is important because it suggests that nudges are more likely to be welfare reducing in individual insurance markets that are not as heavily subsidized as Part D.

Finally, I investigate the importance of accounting for collective decision making in policy evaluations by repeating the policy analysis with and without accounting for the way that couples interact in their decision-making. In a conventional model that assumes spouses choose individual insurance plans independently, singles are hurt less after the nudge. The reason is simple: spouses are now more risk averse since they are not able to share risks. This increase in their risk premia makes them more prone to select the same plans as widows. This decreases the premiums of plans that are also selected by widows since spouses are healthier on average. Following the nudge, only 4% of couples buy the same plan when they choose plans in isolation compared to 95% when they make decisions collectively. Interestingly, I find that when couples choose separately, plans are less adversely selected with only moderate increases in premiums.

This paper contributes to several pieces of literature. First, it adds to the literature on behavioral health economics, Chandra, Handel and Schwartzstein (2019), by providing the first evidence on how couples choose health insurance plans. Similar to conventional models of individual decision making in insurance markets, I estimate a stochastic choice model that incorporates inertia, (Abaluck and Gruber, 2011; Handel, 2013; Polyakova, 2016; Ketcham, Kuminoff and Powers, 2016). I extend this literature by providing the first evidence on the prevalence of within-household pooling and show that, like inertia, it has first-order implications for how couples choose individual insurance plans. Further, I demonstrate that pooling can change conclusions about the effects of policies that are intended to help consumers make more informed choices and have implications for adverse selection, building on prior work by the interaction between nudging and adverse selection by (Handel, 2013; Polyakova, 2016; Handel, Kolstad and Spinnewijn, 2019).

My findings also contribute to the empirical literature of Medicare Part D, (Abaluck and Gruber, 2011; Kling et al., 2012; Ketcham et al., 2012; Ericson, 2014; Ketcham, Lucarelli and Powers, 2015; Abaluck and Gruber, 2016; Ketcham, Kuminoff and Powers, 2016; Polyakova, 2016; Ketcham, Kuminoff and Powers, 2019). However, my work differs from these prior studies in two important ways. First, I provide the first analysis of how household type affects the demand for prescription drug insurance plans and how different types of households interact in this market. Second, I adopt an expected utility framework and estimate a distribution of risk aversion measures in the Part D population in a novel way. I exploit the similarities between the HRS and the Medicare Part D population to project a distribution of absolute risk aversion parameters that were elicited using hypothetical gamble questions.

Finally, this paper also contributes to the broader literature on how household structure affects household decision making, (Fonseca et al., 2012; Addoum, 2017). The main contribution relative to this literature is the unique financial setting where my spouses are making decisions: individual insurance markets.

The rest of the paper proceeds as follows. Section I briefly review relevant literature on inertia and adverse selection in Medicare Part D. Section II describes the data. Section III shows descriptive evidence of household inertia, plan pooling, assortative mating, and costs. Section IV introduces the stochastic choice model of household type. Section V shows the estimates of risk aversion and model parameters. Finally, section VI describes the different pricing models and counterfactual policies. Section VII concludes.

1 Medicare Part D, Inertia and Adverse Selection

Medicare Part D was established in 2006 and was the largest expansion of the Medicare program since its inception. A novel feature of Medicare Part D, relative to traditional Medicare (Part A and Part B), was the creation of markets in which private insurance companies can sell standalone prescription drug insurance plans (PDP) to Medicare enrollees at prices that are subsidized by the federal government.[2] In 2016, about 40 million Medicare beneficiaries choose to enroll in plans that offered prescription drug coverage (70% of the Medicare population) and had average spending of 2,130 dollars per enrollee, (Hoadley et al 2016). From those 40 million, 60% were enrolled in a Part D prescription drug plan (PDP) while the rest where enrolled in Medicare Advantage.

The U.S. Centers for Medicare and Medicaid Services divides the United States into 34 geographic regions, each of which offers a distinct menu of plans. Insurance companies can offer multiple plans in a single region; they can offer different plans in different regions; and they can change the attributes of a given plan in a given region (e.g. premiums, co-payment rates) from year to year. Thus each region-year comprises a distinct market in the sense that all Medicare beneficiaries within the market choose among the same menu of plans. The default for new Medicare beneficiaries is to be uninsured. They must enter the market and actively choose a plan to become insured. Their choice becomes their automatic default plan for the following year. They will be re-enrolled in the same plan unless they actively switch plans, opt out of the market during the annual open enrollment period or if their plan exits the market the following year. Importantly, Medicare Part D, like Medicare Adavantage and Medigap, is a market for individual health insurance. When married seniors buy plans, they have to buy individual plans for each spouse. No family plans or premium discounts for families are offered.

CMS regulates the PDP markets in several ways. First, people who enroll after age 65 are required to pay a penalty that increases their monthly premiums. Second, premiums are subsidized by the federal government and risk-adjusted in order to prevent adverse selection and "cream skimming". Third, firms that want

[2]The other option for Medicare enrollees to get coverage for prescription drug expenses is to purchase Medicare Advantage drug plans.

to participate in the market must adhere to a regulated bidding process. Each year, firms submit bids that reflect the cost to supply the basic benefits to a person of average health.[3] The difference between the plan's bid and the government subsidy determines the plan premium that enrollees must pay.[4] Once a plan submits its bid for the upcoming year, it must accept all enrollees at the predetermined premium.[5] Finally, the payment that each firm receives for insuring an individual is equal to the bid, risk-adjusted by the individual's health condition. Thus, subsidies and risk-adjustment have key implications for costs, premiums and insurance payments in the Part D markets.

Although these policies induced most Medicare enrollees to participate in the market, they did not prevent some generous plans from suffering death spirals, (Heiss, McFadden and Winter, 2009). A plan suffers from an adverse selection death spiral when the plan's market share and premium start experiencing a rapid decrease and increase respectively. Indeed, most plans that were offering generous coverage in 2006 were no longer available in 2009, (Polyakova, 2016), suggesting a considerable degree of adverse selection. Polyakova (2016) confirms this by constructing a non-parametric test in the spirit of Chiappori and Salanie (2000). She finds that most generous plans attracted individuals with higher annual expenditures. The definition of adverse selection used in these studies is similar to the one I will employ. A plan is defined to be adversely selected relative to a baseline scenario if the expected costs of the plan is higher relative to the baseline scenario. This difference in costs will depend on the pool of consumers who choose the plan.

Another striking feature of the PDP market is the high rates of inertia. Kling et al. (2012), Polyakova (2016), Ketcham, Kuminoff and Powers (2016), Ho, Hogan and Scott Morton (2017) document that enrollees rarely switch plans, with 90% of them passively reenrolling in their default option when available. This fact sparked considerable research on trying to understand the consequences of this behavior for market outcomes and welfare (e.g. Ericson, 2014; Ketcham, Kuminoff and Powers, 2016; Polyakova, 2016; Ho, Hogan and Scott Morton, 2017). Some of these studies estimate the amount of money that enrollees would have to be paid ex-ante to

[3]The basic benefit parameters are set by CMS each year. They consist of three numbers: an annual deductible, an initial coverage limit and an out of pocket catastrophic threshold.

[4]Enrollees who qualify for the Low Income Subsidy (LIS) pay less than this resulted premium.

[5]See Stocking et al (2014) for more details about the bidding process.

switch to another alternative. For example, Polyakova (2016) estimates a monetary value of status quo inertia around 1,159 dollars and Ketcham, Kuminoff and Powers (2016) estimate a range between 809 and 3,660 dollars depending on enrollees' characteristics. These estimates are generally interpreted as reflecting a combination of search and switching costs, and inattention.

Evidence on the quantitative importance of inertia motivated the study of policies that nudge consumers toward different choices. For example, Polyakova (2016) explores the welfare consequences of nudging Part D enrollees away from their default plans. Her results suggest moderate adverse selection and higher welfare gains from better plan-person matches. Ketcham, Kuminoff and Powers (2019) compare the distributional welfare consequences of three specific policies that nudge consumers: restricting menus, smart defaults and providing personal information about potential savings from switching plans to Part D enrollees. They conclude that although none of these policies are Pareto efficient, personalized information benefits most enrollees.

I advance this literature in several ways. First, I study how couples choose plans and how their choices affect the trade-off between nudging and adverse selection. Second, I use expected utility to consider the role of risk aversion, how it is distributed across different type of households, and how it is correlated with consumer risk. These features are crucial to predict how polices that aim to nudge consumers toward enrolling in certain types of plans (e.g. lower cost, greater risk protection) will affect adverse selection, (de Meza and Webb, 2001; Cutler, Finkelstein and McGarry, 2008; Finkelstein and McGarry, 2006). Third, I study how nudging policies interact in markets with standard regulations like premium subsidies and risk-adjustment payments. With a stylized model of plan pricing I am able to study how risk adjustment payments and subsidies affect enrolees' sorting patterns.

2 Data

2.1 Medicare Part D

I begin with a random 20% sample of all Medicare beneficiaries age 65 and above who participated in Part D market between 2006 and 2010. This sample comprises more than two million individuals. I also observe all of the financial characteristics of plans including plan premiums, deductibles and coinsurance rates, as well as non-financial characteristics including brand names and CMS star-ratings.[6] Finally, I observe the quantities of each specific drug each person purchased each year under their chosen plan.

Table 1 shows summary statistics for the evolution of the choice set over the first five years of the program. The number of plans and brands change each year. This change in plan menus will be crucial for the identification of status quo inertia. The other striking feature about the market is the substantial variation in annual premiums.

Table 1: Medicare Part D 2006-2010

	2006	2007	2008	2009	2010
Average # Plans	44	56	55	50	47
Average # Brands	20	25	23	24	21
Mean Premiums ($)	450	440	478	547	566
sd Premiums ($)	160	185	238	245	235

Notes: Table 1 shows summary statistics of the Medicare Part D market for the first five years of the program. The average number of plans, brands and premiums are calculated across regions.

2.2 CMS Administrative Records

I match the Part D data to administrative records containing rich information on chronic medical conditions, demographics, annual residential location at the level of a zip-9 code, dates of death, and last names. The CMS records also include a beneficiary identification code (BIC) that specifies the basis of the individual's eligibility for cash payment programs, mainly Social Security. When the individual qualifies under another person's account, e.g. as a spouse, the code identifies the type of relationship between the individual and the primary beneficiary. In particular, widows and divorced people, are entitled to claim their ex-spouses social

[6]The Centers for Medicare Medicaid Services (CMS) created a Five Star Quality Rating System that rates Part D plans. Ratings are between 1 and 5, 5 being the highest, for health plan quality based on measurements of customer satisfaction and quality of care the plan delivers.

security benefits.[7] I will use this variable, BIC, to identify singles in the CMS records.

2.3 MCBS

I merge the Part D data with survey responses for all individuals who participated in the Medicare Current Beneficiary Survey (MCBS) between 2005 and 2011. I use the MCBS to compare my match rates of couples and singles with the true rates in the Medicare population.[8] From here I can obtain the marital status of approximately 3,500 seniors.

2.4 HRS

In order to estimate the degree of risk aversion for each individual in the Part D sample, I use a set of questions that were specially designed to elicit risk aversion parameters on the Health and Retirement Study (HRS). The HRS is a longitudinal panel study that surveys a representative sample of approximately 20,000 seniors in the United States. Importantly, the survey contains rich information on demographic characteristics and prescription drug expenditures. While I am unable to match individuals across the HRS and Part D samples, I leverage the fact that they describe the same population. I first estimate a distribution of absolute risk aversion measures in the HRS as a function of individual demographics and prescription drug spending. Then I project this distribution onto the Part D sample. This procedure for generating imputed variables in CMS-samples using HRS data is similar to the approach used in Fang, Keane and Silverman (2008).

[7] In general, widows can claim their deceased spouse's benefits when they are age 60 or older and they don't remarry before age 60. Divorced people can also claim benefits based on their ex-spouses work. Generally, they can do it if the following conditions are met; they reach age 62, the marriage lasted 10 years or longer, they are still unmarried, and the benefits they are entitled through their ex-spouses work are higher than the benefit they are entitled through their own work.

[8] The MCBS operates as a rotating panel survey with rich information on the demographics of people in Medicare.

2.5 Risk Scores

I use data on each enrollee's chronic medical conditions to calculate risk scores using the RxHcc Risk Adjustment Model developed by CMS. This model was created to adjust CMS's subsidies to insurance companies offering Part D plans. The scores are non-negative numbers normalized to be one for the average risk score in the Medicare population. Individuals with higher scores have higher expenditure risk.[9]

2.6 Identifying couples and singles

To the best of my knowledge, this is the first paper to identify couples in CMS administrative data. I define a "couple" as a pair of beneficiaries, one female and one male, who have the same last name and who share the same residential ZIP+9 code during the same year. The rationale for the matching algorithm is simple. First, zip-9 codes are close to street addresses in terms of spatial precision; each code corresponds to a single mail delivery point such as a unique address, one floor of an apartment building, or one side of a street on a city block. Equally important, only 17% of women who married in the 1970s kept their maiden names, (Cain and Derek, 2015). This was a spike relative to prior and future years given the rise of the feminist movement. Moreover, according to the US Census Bureau, the median age of first marriages in 1970 was 20.6 years old for women. A woman who was 65 years old in my study period, 2006-2010, was at least 30 years old in 1970 implying that most of them got married before 1970. Thus, the majority of women in my sample, if married, took their husband's last name.

I rely on several variables to identify singles separately from individuals who are married to someone who was not present in my 20% random sample of beneficiaries. First, to identify widows and divorced women I use the BIC variable described earlier. The BIC is not ideal to identify single men since most men, whether single or married, claim their own social security benefits. Most of my sample of widowers are identified using the death dates of wives of men that are determined to be married according to my algorithm. Finally, I augment the sample of divorced men using the MCBS sample.

[9] See Robst, Levy and Ingber (2007) for more details about the model.

Table 2 assesses the performance of my matching algorithm by comparing the total number of couples that I identify in the Medicare Part D sample each year with the total number of expected matches given the demographic information in MCBS. According to MCBS, 54% of people in Medicare Part D are married. Using this fact and the 20% random sample of Medicare Part D enrollees, I use a simple back-of-the-envelope calculation to estimate how many couples I should expect to observe in my sample. Therefore, the statistical prediction for the number of matches for each year is $N_y 0.54 * 0.2 * 0.54$ where N_y is the size of the random sample of individuals in Part D each year.

Table 2: Couples in Medicare Part D Sample: MCBS vs Algorithm

	2006	2007	2008	2009	2010
Back-of-the-envelope	74,564	77,919	78,292	80,242	80,005
Number of matched couples	73,500	76,696	78,867	82,466	82,880

Notes: Table 2 compares the number of matches I should expect according to MCBS ("Back-of-the-envelope") and the final number of couples in my sample following the algorithm.

The algorithm comes remarkably close to matching the statistical prediction. This makes sense given that for this cohort the majority of wives took their husband's last name.

Finally, table 3 summarizes the demographic variables for each type of household. The shares on marital status reveal an interesting feature about this market; while 54% are married couples, roughly 30% are widows. This means that the preferences and behavior of these two types of households are likely to drive market outcomes.

Table 3: Summary Statistics: Demographics in 2006

	singles	wife	husband
age (mean)	80	73	76
white (%)	95	94	94
total CC (mean)	8	7	7
risk score (mean)	1.04	1.01	0.98
male (%)	4		
divorced (%)	7		
widow/er (%)	92		
observations by year	148,245	68,549	68,549

Notes: Table 3 shows summary statistics of main demographics variables of Medicare Part D enrollees. The first data column shows demographic variables, marital status and health conditions of single individuals. "total CC" shows the mean number of chronic conditions for each type of household. The the last two columns describe demographics variables and health conditions of members of married couples.

The table shows that singles have worse health on average. This is not surprising since they are on average older than spouses. The demographic characteristics of enrollees will be important to understand not only their costs but also their preferences, e.g. risk aversion. Importantly, insurance companies are not allowed to price age or any other characteristic of enrollees in this market.

3 Descriptive Evidence

3.1 Inertia and Pooling

Inertia is a common feature of consumer choice in many markets, (Samuelson and Zeckhauser, 1988). In Medicare Part D, Ketcham, Kuminoff and Powers (2016), show that 90% of individuals choose their default plans each year. Table 4 shows the share of households who choose their default plan by household type from 2007 to 2010. Consistent with prior literature, the fraction of households who stick with their previous choice is on average 90%. Divorced men are the most reluctant to stitch, with 97% of them choosing the default plan. For couples, the figure is slightly smaller: 85%. In other words, 85 percent of couples decide to keep the same plan combination as last year. I also calculate the share of couples who enroll in the husband's default plan (but not the wife's) or who enroll in the wife's default plan (but not the husband's). Both figures are 3%.

Table 4: Inertia in Medicare Part D (2007-2010)

Inertia	Share (%)
singles choosing default plan	92
divorced women	92
divorced men	97
widow	91
widower	92
couples choosing default plan combination	85
only wife choosing default plan	3
only husband choosing default plan	3

Notes: The first six rows of the table table report the fraction of enrollees by type of household who re-enroll in their default plans. The last two rows show the fractions of couples where only one member chooses the incumbent plan.

The table reveals that households types are fairly homogeneous in terms of inertia. This is striking since they are likely heterogeneous in terms of costs and preferences. The fact that heterogeneous households switch at the same rate underscores the pervasive nature of this behavior.

Table 5 shows the share of couples who enrolled in the same plan. Overall, 78% of couples buy the same plan. In principle, this could be explained by partners aging into Medicare in different years and the younger spouse choosing the older spouse's default plan. However, the second row shows the same pattern with 76% of couples pooling in 2006, the first year of the program in which couples entered the market and purchased their initial plans simultaneously. Strikingly, this figure hardly changes when I focus on couples with different health needs. The last four rows of the table divides couples based on the similarity of the spouses' risk scores. "Same Risk" describes couples in the same quartile of the distribution of risk scores. “Adjacent risk quartiles” are couples where spouses are in adjacent quartiles. “Nonadjacent risk quartiles I” are couples where the spouses are either in the first and third quartiles or in the second and fourth quartiles. “Nonadjacent risk quartiles II” are couples where one spouse is in the first quartile and the other is in the fourth quartile. Moving down the last four rows shows that the rate of pooling hardly changes as spouses increasingly differ in terms of their prescription drug risk. The fact that more than three quarters of spouses with substantially different prescription drug risks decide to buy the same plan suggests that this behavior is related to causes beyond health needs and costs.

Table 5: Couples’ Tendency to Choose the Same Plan

Pooling	Share (%)
couples pooling	78
couples pooling in 2006	76
same risk	80
adjacent risk quartiles	77
noadjacent risk quartiles I	76
noadjacent risk quartiles II	75

Notes: The table shows the share of couples who decide to buy the same plan. “Same Risk” corresponds to couples in the same quartiles of the distribution of RxHCC risk scores. “Adjacent risk quartiles” are couples where spouses are in different adjacent quartiles. “Nonadjacent risk quartiles I” are couples where one spouse is in the first, or second quartile and the other spouse is in the third and forth quartile respectively. “Nonadjacent risk quartiles II” are couples where one spouse in the first quartile and the other is in the forth quartile.

Why do so many couples buy the same plan? A vast literature studies why individuals tend to choose their status quo options. Starting with Samuelson and Zeckhauser (1988), the literature has tended to divide mechanisms into two main categories: rational decision-making and cognitive misperceptions. Examples of the former are costly information acquisition or uncertainty about plan features. Both examples imply that plans must be discovered, leading to search rules and cutoff strategies. An example of the second category is loss-aversion, with the incumbent plan being the reference point such that losses from switching will be weighted more than gains from the same action.

The same two sets of mechanisms can explain why couples tend to buy the same plan. There are several reasons why it may be optimal for spouses to choose the same plan. For example, if couples have the same preferences and risk or they are specially matched, e.g. highly risk averse wives married to high cost husbands, then within-household plan "pooling" may emerge endogenously. Bargaining within the household and risk-sharing can also explain why couples buy the same plan. For example, if one spouse is more risk averse than the other, he could agree to buy a less generous plan if the less risk averse spouse is willing to bear most of the risk. In this scenario, the less risk averse spouse sacrifices more private consumption in the bad state and consumes more in the good state. Division of tasks within the household may also explain this behavior. If the couple splits duties to save time and effort, the spouse who is in charge of choosing insurance plans may find it optimal to choose a single plan for both spouses if searching is costly for the same reasons that lead to inertia. In terms of cognitive misperceptions, a possible explanation is the convergence of beliefs of each spouse about their own risks. This may occur, for example, if a specific chronic condition afflicting one member has salience effects over the other spouse, (Fadlon and Nielsen, 2019).

I do not attempt to identify the relative importance of the various mechanisms that cause pooling. Instead, I measure how large the combined effect of these mechanisms must be to rationalize couples' observed choices. Identifying model parameters designed to capture the tendency to pool requires characterizing the distribution of risk aversion among single and couples, ex ante differences in expected costs, and rules for risk sharing within households. Each of these features is discussed below.

3.2 Household Costs and Residual Costs

Table 5 suggests that assortative mating on prescription drug use does not explain why couples decide to buy the same plan. Nevertheless, understanding the degree of assortative mating may be important for policy. In the education literature for example, assortative mating on educational attainment is of interest because it has implications for household income inequality, (Fernández, Guner and Knowles, 2005; Eika, Mogstad and Zafar, 2019). Similarly, assortative mating in health may contribute to household health inequality, (Fleurbaey and Schokkaert, 2011). Further, predicting market outcomes and welfare consequences of policies that nudge consumers toward different choices requires knowing the costs of couples and how they are related to costs of other type of households.

To better understand the degree of assortative mating in prescription drug expenditure, I compare three different measures in 2006. First, I assign each spouse to their corresponding quartile of the distribution of risk scores at the beginning of the year. Then I compare the Pearson correlation coefficient of these variables with the correlation coefficient estimated for randomly assigned couples from the same geographic area. Panel A of Table 6 shows the correlation of risk scores for actual couples, the correlation of risk scores for random couples from the same state and the correlation of risk scores for random couples from the same zip-5 code. Panel B of the table shows the same statistics but calculated based on quartiles of total cost under each plan in 2006. The two measures differ in that the second measure is affected by the choice of plan while the first is not.

The correlation coefficient for actual couples is 2.5 times larger than the correlation coefficient for randomly matched couples from the same zip-5, and 13 times larger than the correlation of random matches from the same state. The correlation among actual couples is small relative to the measures of assortative mating estimated in the education literature. In Fernández, Guner and Knowles (2005) for example, the Pearson correlation coefficient describing assortative mating in education in different countries ranges from 0.32 to 0.76. Further, compared to the education setting my estimates are more likely to be increased by changes in behavior after marriage that would increase the estimated degree of assortative mating in health.

Predicting how the market will evolve after a specific policy also requires un-

Table 6: Assortative Mating - Prescription Drug Expenditure

Actual couples	Random couples	
	same ZIP5	same state
A. Risk Score Correlation		
0.147	0.061	0.011
B. Prescription Drug Expenditures Correlation		
0.261	0.104	0.018

Notes: Panel A shows the Pearson correlation coefficient of risk scores of actual couples, the correlation of risk scores of randomly matched couples from the same state and the correlation of risk scores of randomly matched couples from the same zip-5 at the beginning of 2006. Panel B of the table shows the same statistics but calculated with quartiles of total costs under each plan in 2006.

derstanding how the costs of married couples compare to the costs for other types of households. As shown in Table 3, widows constitute the majority of single households. According to MCBS, they represent 30% of the market. Table 7 compares the distribution of costs of wives, husbands, couples and widows. Costs are measured as total prescription drug expenditures minus the out of pocket expenditure of each household. This difference represents the cost that insurance companies incur.

Table 7: Moments of the Cost Distribution for Spouses, Couples, and Widows

Costs	wife	husband	couple	widow
10 percentile	0	0	20	2
25 percentile	56	55	195	207
median	448	497	650	813
75 percentile	1,271	1,359	1,165	1,583
90 percentile	1,845	1,890	1,702	2,020
mean	868	873	871	1,116

Notes: Table 7 compares the distribution of costs of wives, husbands, couples and widows. Costs are measured as total prescription drug expenditures minus the out of pocket expenditure of each household. This difference represents the cost that insurance companies incur.

The table shows that the average cost of wives and husbands is smaller than the cost of widows. If the majority of couples buy the same plan, then we can think that the evolution of the market will be driven by the behavior of these two types of households, with married couples being the "good type" and widows being the "bad type" in the sense of Rothschild and Stiglitz (1976). Importantly, since the average cost of widows exceeds the average costs of each spouse, the presence of widows in the market makes the degree of assortative mating less important for predicting market outcomes when couples pool. In general, the difference in the cost of widows relative to the cost of couples will be positive, regardless of their decision to pool. Widows are on average $245 more costly than married couples.

As noted earlier, the process for risk adjusting payments to insurance companies is an important feature of the Part D markets. The costs shown in Table 7, measure the total costs but not the residual costs that matter for insurance companies' profits, (Layton, 2017). Without risk adjustment, premiums will likely reflect the average cost of the enrollee pool. Layton (2017) shows that in the presence of risk adjustment, premiums will reflect average residual costs, which are defined to be costs that are not predicted by the risk adjustment model. To be more concrete, under risk adjustment the premium of plan j will be:

$$\text{Premium}_j = E(\text{cost}_j) - E(\text{RA}_j) + E(\text{cost}) \tag{1}$$

Here $E(\text{cost}_j)$ reflects the average cost of the enrollees who selected plan j, $E(\text{RA}_j)$ the average risk adjustment payments of the pool and $E(\text{cost})$ reflects the average cost of the market. Equation 1 implies that the difference in premiums will reflect the difference in average residual costs, $E(\text{cost}_j) - E(\text{RA}_j)$. Prior studies have shown that the risk-adjustment model that CMS uses for Part D (RxHCC Model) tends to overpredict costs for beneficiaries with low actual costs, and underpredict costs for beneficiaries with high actual costs, (Hsu et al., 2009). These systematic prediction errors will likely distort the differences in residual costs relative to total costs. Table 8 illustrates this point by showing the average costs and residual costs of couples and widows, and the differences between them. With imperfect risk adjustment payments, the difference in residual costs is 35% higher than the difference in total costs.

Table 8: Residual Costs for Couples vs Widows

	Total Costs			Residual Cost		
	couple	widow	difference	couple	widow	difference
mean	871	1,116	245	121	453	332

Notes: Table 8 shows the average costs and residual costs of couples and widows and the differences between them. Residual costs are the costs that are not predicted by the risk adjustment model.

This difference in total costs and residual costs is important because it may exacerbate adverse selection if couples and widows select different plans. In section 6, I explore the consequences of this wedge in the context of a policy that nudges consumers toward different choices. Importantly, costs are just one factor in the calculations. The preferences of these two type of households also matter for predicting the evolution of the market and how it responds to different regulations. More specifically, the distribution of risk aversion across households is crucial for understanding how households will react.

4 Empirical Framework

4.1 Model

4.1.1 The Choice Set

Consumers are modeled as choosing lotteries of prescription drug expenditure, where a lottery is defined by a distribution of prescription drug expenditures under all possible health states of the world and a set of probabilities for realizing those states. To construct these lotteries I rely on several variables contained in the CMS Administrative records, including the diagnosis dates of more than 30 chronic conditions from CMS Chronic Condition Data Warehouse. Specifically, I use knowledge of the health conditions and demographics of each enrollee, to calculate their individual risk scores using the RxHcc Risk Adjustment Model developed by CMS.[10] I define a "cell" as a set of individuals with the same risk score in year T-1 who live in the same CMS region. Ex-ante distributions of out-of-pocket (oop) expenditures of each plan and type in year T are generated with the realized oop costs in year T of all beneficiaries that belong to the same cell. This means that the oop expenditure of each beneficiary is a possible state of the world for all beneficiaries that belong to the same cell. This actuarial method of creating oop distributions has been used extensively, (Pauly and Zeng, 2004; Abaluck and Gruber, 2011; Handel, 2013; Ketcham, Kuminoff and Powers, 2016).

In order to construct the ex-ante distributions of oop expenditures of every plan-person match, I make the standard assumption of no moral hazard. I use a cost calculator developed by Ketcham, Lucarelli and Powers (2015) to construct counterfactual out-of-pocket expenditures for the bundle of drugs that each beneficiary purchased under all of the plans in the beneficiary's choice set. This is essentially the same as the approaches used in Abaluck and Gruber (2011), Abaluck and Gruber (2016), Ketcham, Kuminoff and Powers (2016), and Ketcham, Kuminoff and Powers (2019). The no moral hazard assumption in these studies is justified by the small drug-specific price elasticities estimated in the literature and the high persistence of drug use, both of which are indicators of moderate moral hazard, (Abaluck,

[10] The two demographic variables that enter in the RxHcc model together with the chronic conditions, are age and gender.

Gruber and Swanson, 2018). As long as the presence of moral hazard is mild the estimated distributions will approximate the true distributions.

The oop expenditure of each beneficiary can then be used to construct the empirical CDF for plan j and type t as follows:

$$\hat{F_{jt}}(x) = \frac{1}{n_t}\sum_{i=1}^{n_t} 1(X_{ij} \leq x) \tag{2}$$

In the equation n_t is the number of observations of type t, i.e. the number of people that belongs to that cell, x is a non-negative number that belongs to the support of the distribution of out-of-pocket expenditure and $1(X_i \leq x)$ is an indicator function for whether realization i in plan j is less than x.[11] I assume that the distributions of out-of-pocket expenditure implied by each plan and type belong to the bounded and common support $[a, b]$.[12] If a plan has a smaller realized support I define the density function of that distribution to be zero outside this range.

To construct the distributions of out of pocket expenditures for couples I use copula methods.[13] Intuitively, a copula expresses a joint distribution as a function of marginal distributions and a correlation parameter. I use Gaussian copulas to generate the bivariate distribution of oop for the couple as a function of the marginal distribution of each spouse. The Gaussian copula form is $C(u_1, u_2, \rho) = \Phi_b(\Phi^{-1}(u_1), \Phi^{-1}(u_2); \rho)$, where Φ_b is the CDF of the standard bivariate normal distribution and Φ^{-1} is the inverse CDF of the standard normal distribution. The copula is a function of a correlation parameter ρ and $u_i = F_i(x)$, the range of the marginal CDF distribution function of each spouse. Appendix A provides a detailed description of the steps used to construct the distribution of couples' oop expenditures and estimate ρ.

Under this formulation, the only parameter to be estimated is ρ.[14] ρ captures the joint dependency of both distributions $F_i(x)$ which could, in principle, be very

[11] Like Handel (2013) I require the minimum cell size to be 75 individuals.

[12] Here a will be the smallest realization of out-of-pocket expenditure among all plans and types while b will be the maximum. I will discretize the support in r pieces as is often done when working with empirical CDFs.

[13] See Trivedi and Zimmer (2006) for an introduction to copula methods in economics.

[14] We should not interpret this parameter as a reflection of assortative mating. The later would be captured by how similar are the $F_i(x)$ of each couple.

different from each other. An intuitive example of what ρ measures is the "broken heart syndrome" in life insurance, in which the death of a spouse reduces the survival probability of the other spouse, (Denuit et al., 2005). For tractability, I assume that ρ is constant across diseases. This assumption is supported by medical evidence that people with partners that have ischaemic heart disease, diabetes, or experienced a stroke have no increased risk of contracting the disease themselves. While this is not true for asthma, depression, and hypertension, these diseases are likely to be less expensive to treat (Hippisley-Cox et al., 2002). I estimated $\hat{\rho}$ to be equal to 0.3 (p=0.0000). This means that couples' risk exhibits a positive dependence, consistent with the intuition for broken heart syndrome.

I follow standard practice in assuming that the relevant distributions from which households are choosing are the ones estimated by the researcher. This assumption could be violated for two reasons. The first is private information. Specifically, the estimated F_{ij} and the true distributions could differ if enrollees possess information that is not available to the researcher. This is relatively minor concern for my analysis because I observe detailed information on chronic condition diagnoses and other demographic characteristics that together with the RxHCC software allows me to calculate risk types for each enrollee. Further, I focus exclusively on a very specific type of medical risk: prescription drug expenditures. Estimating ex-ante distributions of plans that cover many types of medical services like surgery, hospitalizations and doctor visits would require more information. A second reason why F_{ij} could be substantially different from the distribution determining consumer choice is because of systematic differences in subjective beliefs. Without a complementary survey eliciting subjective beliefs of prescription drug expenditures, it is impossible to assess the validity of this assumption. Thus, I maintain the assumption that subjective beliefs match objective beliefs.

4.1.2 Preferences

Financial markets exist because people have different tastes for risk. Thus, to understand how demand for insurance will change in response to a prospective policy it is essential to know the degree of risk aversion, how it is distributed across households and the extent to which it is correlated with household risk.

How individuals feel about taking risks is also necessary to understand how groups, like couples, make joint decisions in risky environments. Within the tradition of methodological individualism it is individuals and not groups, who are presumed to have preferences.[15] How groups make choices depends on the preferences of their members and how their members interact with each other. The interaction could be by a voting rule, within household bargaining or any other mechanism.

To understand how different types of households decide among insurance plans and how policies will affect their decisions, I represent household behavior with a stochastic choice model. In other words, consumers' choices will be consistent with a deterministic core theory, specifically expected utility, plus a shock, (e.g. Harless et al., 1994; Hey and Orme, 1994; von Gaudecker, van Soest and Wengstrom, 2011). The shock is meant to represent errors in the decision process of households when comparing two plans.

For the deterministic component of choice I use exponential utility which implies constant absolute risk aversion (CARA). This parametric form has many advantages. First, it allows the household to be modeled as a representative agent where the household's risk aversion parameter is the harmonic mean of each spouses risk aversion parameter divided by two. This representation is observationally equivalent to a collective model of the household, (Chiappori, 1992). It is also equivalent to group preferences under uncertainty as in Harsanyi (1955) with constant Pareto weights across the study period.[16] Importantly, if couples share risk efficiently, their choices will conform with this utility specification, (Bone, 1998).

More specifically, if both members of the couple have CARA preferences with risk aversion parameters σ_w and σ_h, then the couple can be represented with a utility function of the following form:

$$u_c(x) = -e^{-\sigma_i^* x}, \text{ where } \sigma_i^* = \frac{1}{\frac{1}{\sigma_w} + \frac{1}{\sigma_h}} \tag{3}$$

This representation captures the fact that group risk aversion is derived from

[15]See Chiappori and Mazzocco (2017) for a discussion of methodological individualism and its implications in the unitary approach of household preferences.

[16]In general, additional information on private consumption of each member of the couple and changes in distribution factors are needed to identify Pareto weights, (Chiappori and Mazzocco, 2017).

individual risk aversion. Another advantage of this particular parametric form for utility is that it will allow me to compare my results directly with previous studies that used CARA specifications to depict household-level choices among employer sponsored insurance plans that offer coverage for employees, spouses, and their children, (Handel, 2013; Handel and Kolstad, 2015).

If consumers adhere completely to expected utility, then when they first enter the market they will choose the plan that maximizes the certainty equivalent (CE).[17] However, the random element added to their utility function implies that households may choose plans of lower value. For example, when comparing two plans j and j', household i will select plan j whenever:[18]

$$\text{CE}(L_{jhi}, \sigma_i) - \text{CE}(L_{j'hi}, \sigma_i) + \lambda_h \epsilon_{jj'hi} \geq 0 \tag{4}$$

$\epsilon_{jj'hi}$ are independent household plan logistic shocks, i indexes the household (which may be comprised of an individual or a couple), h indexes the household type, e.g. couples or singles. For a couple, L_{jhi} represents the lottery associated with plan combination j, given the couple's joint distribution of potential health shocks.

Insurance plan enrollment is repeated each year. As seen above, during open enrollment most households default into their incumbent plans and most couples enroll in the same plan. Equation 5 shows that households will choose the default plan combination j over j' if:

$$\text{CE}(L_{jhi}, \sigma_i) + K_h 1_{d=j} + 1_{j=p}\Omega - \text{CE}(L_{j'hi}, \sigma_i) - 1_{j'=p}\Omega + \lambda_h \epsilon_{jj'hi} \geq 0 \tag{5}$$

$1_{d=j}$ is an indicator if the plan or plan combination is the household's default plan. Similarly, $1_{j=p}$ is an indicator for whether couples choose the same plan. This formulation highlights an advantage of using certainty equivalents as a cardinaliza-

[17] With exponential utility, $\text{CE}(L, \sigma) = \frac{1}{\sigma} \ln\Big(\text{E}(e^{\sigma x})\Big)$.

[18] In equation 4 the plan premium is included in the certainty equivalent.

tion of preferences. It allows us to measure the values that particular household types attribute to status quo plans and plan-pooling in monetary terms using the parameters K_h and Ω.[19] In particular, the way I am measuring status quo inertia is identical to Handel (2013) and Handel and Kolstad (2015).[20]

The interpretation of λ_h, the scale of the logistic shock, is important and related to the interpretation of $\epsilon_{jj'hi}$. In random utility models, $\epsilon_{jj'hi}$, is typically used to represent latent attributes that provide utility to households. Under this interpretation λ_h determines the relative importance of expected utility for household decision-making compared to all other non-modeled attributes. If, however, we treat EU as a normative decision-theory in the sense that households should behave as EU maximizers then $\epsilon_{jj'hi}$ are interpreted as a "mistake" and λ_h as a measure of conformity with expected utility. In my main specifications $\epsilon_{jj'hi}$ is used to represent errors in the decision process. This interpretation is meant to facilitate the counterfactual scenarios I explore later in the paper, in which a regulator who cares paternalistically for consumers welfare will attempt to nudge consumers to conform with expected utility by introducing a generic policy that reduce the magnitude of λ_h.

4.2 Identification

4.2.1 Risk aversion

I first estimate a distribution of individual-specific parameters describing absolute risk aversion as a function of demographics and prescription drug spending using data from the Health and Retirement Study (HRS). Then I use observable demographics to project this distribution onto the Medicare Part D population. I use a set of questions in the HRS that were designed to elicit risk aversion by asking each individual to choose among hypothetical monetary gambles.

The HRS data allow me to overcome the problem explained in Apesteguia and Ballester (2018) that risk aversion cannot be identified in many discrete choice set-

[19]Equation 5 can alternatively be represented similarly to a random utility model: $\beta_{0h}\text{CE}(L_{ji}, \sigma_i) + \beta_{1h}1_{d=j} + \beta_{2h}1_{j=p} - \beta_{0h}\text{CE}(L_{j'i}, \sigma_i) - \beta_{2h}1_{j'=p} + \epsilon_{hi}$ with $\frac{\beta_{1h}}{\beta_{0h}} = K_h$, $\frac{\beta_{2h}}{\beta_{0h}} = \Omega$ and $\beta_{0h} = \frac{1}{\lambda_h}$.

[20]They define inertia in terms of a "bidding price". However, given that they also use a CARA specification and assume independence between the distribution of out of pocket expenditures and inertia, both measures coincide, (Pratt, 1964).

tings. The problem is that CARA and CRRA preferences embedded in stochastic choice models can generate the same choice probabilities with different values of risk aversion. Moreover, estimating the risk aversion level of each household member is necessary for predicting how choices would change if individuals were to choose in isolation. Thus, I assume that the hypothetical gambles that were used to elicit risk aversion parameters for a random sample of individuals in HRS capture spouses' levels of risk aversion in scenarios where they can't share risks. This assumption is consistent with the design of the survey questions, which are described in more detail below.

Using stated-preferences methods to elicit risk aversion parameters, such as hypothetical gambles, instead of revealed-preferences methods has well-known tradeoffs, (Diamond and Hausman, 1994; Beshears et al., 2008; Mata et al., 2018). While stated preferences methods are usually better in controlling for possible cofounders, revealed preference methods are often thought to perform better in real-world scenarios that are difficult to represent on a survey or in the laboratory. Given these tradeoffs, many studies have investigated the validity of HRS risk measures and have found a strong relationship between these measures and individuals' financial decisions, (Mazzocco, 2004; Kimball, Sahm and Shapiro, 2008). Finally, my approach to transferring risk aversion parameters from the HRS to CMS assumes that the levels of risk aversion for individuals are constant across domains. So that risk aversion parameters elicited with monetary gambles can be used to assess risky choices of health insurance plans. While there is some debate over this assumption (Barseghyan, Prince and Teitelbaum, 2011), Einav et al. (2012) find that individuals' willingness to take risk relative to their peers remains stable across domains.[21]

I elicit risk aversion parameters using the following questions that were asked in the 2004 HRS wave, two years prior to the introduction of Medicare Part D:

Suppose you have an additional USD 10,000 saved for the future. You can choose to invest this money one of two ways. One is to invest in a government bond that will be worth USD 10,000 in two years for sure. The other way is to invest in a

[21] This result is important for the present paper because I will be comparing status quo inertia for different types of households: widows, widowers, divorced women, divorced men, and couples. Importantly, the monetary estimates will depend on the different levels of risk aversion of each type of household. As long as risk preferences, relative to these demographic groups, are stable across domains; the relative size of status quo inertia will be stable as well.

mutual fund that may increase or may decrease in value in the next two years. On average the mutual fund will be worth 20,000 in two years, but has a 50-50 chance of being worth USD 5,000 and a 50-50 chance of being worth USD 35,000. Would you invest your money in the government bond that guarantees you USD 10,000 or in the mutual fund I have just described?

Individuals who choose the riskier option, were then asked:

Suppose instead that the average return on the mutual fund is lower. On average the mutual fund will be worth USD 15,000 in two years, but has a 50-50 chance of being worth USD 5,000 and a 50-50 chance of being worth USD 25,000. Would you invest your money in the government bond that guarantees you USD 10,000 or in the mutual fund I have just described?

If the individual opted for the risk-free option in response to the first question, he would then be asked:

Suppose instead that the average return on the mutual fund is higher. On average the mutual fund will be worth USD 25,000 in two years, but has a 50-50 chance of being worth USD 5,000 and a 50-50 chance of being worth USD 45,000. Would you invest your money in the government bond that guarantees you USD 10,000 or in the mutual fund I have just described?

This procedure identifies lower and upper bounds on the absolute risk aversion parameter. Following the approach described in Barsky et al. (1997), Kimball, Sahm and Shapiro (2008).[22]

After using respondents' answers to assign them to mutually exclusive categories, I use their resulting bin assignments to estimate a continuous distribution of risk aversion. I assume that the distribution of risk aversion is log-normal: log$\sigma \equiv x \sim N(\mu, \phi)$, with the mean $\mu = \mu_0 + \gamma_1 X + \gamma_2 M$ being a function of demographics, X, and different bins of prescription drug expenditure, M. Gender and age will be included in X and the prior year's total expenditure on prescription drugs will be included in M.[23] The probability of being in category j is then:

[22]They use relative gambles that were designed to elicit relative risk aversion coefficients for CRRA preferences. The only difference is that I use a different set of questions.

[23]I group people in four different bins of prescription drug expenditure: people whose annual spending was below \$50, people whose spending was between \$50 and \$500, between \$500 and \$2,500 and people whose annual spending was above \$2,500.

$$P(c = j) = P(\log\sigma_{lj} < x < \log\sigma_{uj}) \tag{6}$$

$$P(c = j) = \Phi((\log\sigma_{uj} - \mu)/\phi) - \Phi((\log\sigma_{lj} - \mu)/\phi), \tag{7}$$

where Φ is the cumulative normal distribution function and σ_{lj} and σ_{uj} denote lower and upper bound of absolute risk aversion of category j. I estimate $\mu_0, \gamma_1, \gamma_2$ and ϕ via maximum likelihood.

4.2.2 Inertia and Plan Pooling

The identification of status quo inertia relies on two main sources of variation in the data. Two sets of enrollees serve as control groups for people who have a status quo plan in their menus. The first group is new enrollees. As noted by Samuelson and Zeckhauser (1988), the active choices of new enrollees capture what the choices of old (and similar) enrollees would have been absent the status quo plan. I have detailed data on chronic conditions for old enrollees and for most of the new enrollees as well. This is one of the advantages of having data in the early years of this market. However, it is important to distinguish enrollees that are new to Part D and enrollees that are new to the entire Medicare system (Part A and B). Because chronic conditions diagnoses are collected for all enrollees who are already in Part A and Part B, I can construct ex-ante distributions of oop for enrollees who are new to Part D but not to the rest of Medicare. This group is formed by enrollees who enrolled late in the market, after turning 65 years old. The second control group is composed of enrollees who are forced to choose actively because their incumbent plan was discontinued. These two groups constitute the “active” choosers who lack a default plan. The second feature of the data that allows me to identify status quo inertia is the continuing change in plans’ menus that happen each year. This was depicted in Table 1. New plans enter the market each year and some old plans exit.

Finally, “willingness to pool” is identified by the active choice of new couples, e.g. the choice in 2006, and couples who switch plans. This is, each year new couples express their preferences for choosing plan combinations with the same pair of plans or choosing plan combinations with different plans. The strength of their preferences for pooling beyond expected utility will be captured by Ω_h.

5 Results

5.1 Risk Aversion

Table 9 reports maximum likelihood estimates for heterogeneity in individual risk aversion from equation 7. A casual interpretation of the estimated coefficients is unnecessary because the purpose of this exercise is ultimately to project the demographic variation in individual risk onto the medicare population. Nevertheless, the coefficients on demographic variables are broadly consistent with causal estimates from previous literature. Women appear to be more risk averse than men, a finding that has been documented several times in different environments, (Borghans et al., 2009). There is less agreement in the literature on how age affects risk aversion. Cohen and Einav (2007) document a U-shaped relation between age and risk aversion across the life cycle while Dohmen et al. (2011) find a positive slope. Both findings are consistent with the positive slope that I estimate for the final years of the life cycle.

Interpreting the coefficients on medical expenditures and comparing them to prior studies is more complicated. First, my estimates could reflect some reverse causality. That is, people who are less risk averse may take less precaution in their daily life choices, like eating healthy food and exercising, which could result in them requiring more medical services. Second, these variables could reflect the medical risk that each bin is exposed to, and impact risk aversion through this background risk channel.[24] It could also represent health shocks that the individual suffered in the previous year, and impact risk aversion through this channel. The empirical literature established that both channels affect risk aversion, (Courbage, Montoliu-Montes and Rey, 2018; Decker and Schmitz, 2016).

[24] Recall that the hypothetical gambles that each individual responds to in the HRS are not specifically about medical expenditures. So from this perspective, prescription drug expenditures are a background risk, (Gollier, Gollier and Christian, 2001).

In any case, the positive correlation between prescription drug expenditure and risk aversion implies that more costly enrollees have a higher willingness to pay for insurance, because of higher monetary expenses and because they are more risk averse. This positive correlation between risk and risk aversion is also present in the auto insurance setting of Cohen and Einav (2007), whereas Finkelstein and McGarry (2006) document a negative correlation in markets for long term care insurance.

Table 9: Estimates for demographic heterogeneity in Risk Aversion

Parameter	Estimates
constant	-15.79***
	(1.12)
male	-2.02***
	(0.25)
age	0.05***
	(0.01)
prescription drug expenditure I: (USD 50-500)	1.01*
	(0.58)
prescription drug expenditure II: (USD 500-2500)	2.55**
	(0.59)
prescription drug expenditure III: (> USD 2500)	2.58***
	(0.59)
standard deviation	5.27***
	(0.10)
Observations	451

Notes: Table 9 shows maximum likelihood estimates (standard errors) of parameters describing heterogeneity in absolute risk aversion based on responses to survey questions in the HRS. The estimates represent the influence of demographic characteristics on the mean and median absolute risk aversion of the HRS population. "Prescription drug expenditure categories I, II, and II" corresponds to different bins of prescription drug expenditures in the previous year.

Finally, I project the median absolute risk aversion parameter for each demographic group and medical expenditure bin onto the Medicare sample.[25] The mean absolute risk aversion of the Medicare population is .0000369 and the median is .0000131.[26] For an economic interpretation of these estimates, Figure 1 shows the distribution of implied risk premia when individuals face a hypothetical gamble in which they can win or lose $900 with the same probability. This hypothetical gamble is scaled to approximately capture the risk an average individual is facing in Medicare Part D, where with $900 is the standard deviation of out of pocket cost in the first five years of the market. The figure shows the distribution of risk premiums as a fraction of $900. For a risk-neutral individual, this number is zero and for someone who is extremely risk averse it is 1. Although most individuals have moderate values for the risk premium, the distribution is right-skewed suggesting a high degree of heterogeneity.

Figure 1: Distribution of Risk Aversion Among the Part D Population

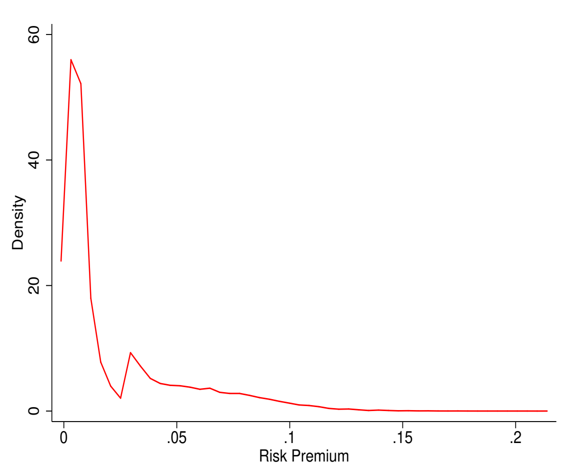

Figure 1 shows the projected distribution of risk premiums in the Medicare Part D population. The risk premium is expressed as a fraction of the $900 gamble. For a risk-neutral individual this number is zero and for someone who is extremely risk averse it is 1.

The estimated distribution of risk aversion parameters allows me to test the

[25] Given my assumption of a log-normal distribution, the median is a better representation of central value tendency than the mean.

[26] This estimates are similar to previous studies, (Cohen and Einav, 2007).

hypothesis that couples tend to pool because people who are highly risk averse tend to be married to partners who are relatively sick, inducing both partners to optimally choose high coverage plans. I test this hypothesis by calculating the following correlation:

$$\text{corr}(\sigma_w - \sigma_h, cost_w - cost_h) \tag{8}$$

A negative correlation means that spouses who are more risk averse are in general married to spouses with higher costs, and vice versa. The estimated correlation coefficient is 0.085, allowing me to reject the hypothesis.

5.2 Inertia and Pooling

The following table shows the estimates for the parameter describing the relative importance of random factors driving choices (λ_h) together with inertia and the value of plan pooling in certainty equivalent terms. I report estimates for the four types of households that represent the largest fractions of consumers in the market; married couples (54%), widows (30%), widowers (6%) and divorced women (5%).

Table 10: Type-specific estimates for status quo inertia and the "willingness to pool"

	Couples		Widows		Divorced Women		Widower	
	Estimates	$P > \|Z\|$	Estimates	$P > \|Z\|$	Estimates	$P > \|Z\|$	Estimates	$P > \|Z\|$
λ	372	0.000	306	0.000	230	0.000	272	0.000
K (inertia)	3,152	0.000	1,975	0.000	1,472	0.000	1,754	0.000
$\Omega(pooling)$	1,584	0.000						
couple last year			1,946	0.000			1,871	0.000
Observations	5,078		14,216		1,134		3,828	

Notes: The first row of the table shows the coefficient on the certainty equivalent, or equivalently the inverse of the variance of the shock. The second row of the table shows the size of the status quo bias. Ω repersents the estimated "willingness to pool". The third row shows the estimated "willingness to pool" for couples. In the fourth row, "couple last year" measures status quo inertia for widowed people who were married in the previous year.

The first row of the table shows the scale of the logistic error for each type of household. The higher the λ_h the less the household type conforms with expected utility maximization, given my assumption about the parametric form of utility. An example can help to illustration the economic interpretation of what these estimates imply for household choices. Imagine there are two plans or plan combinations: A and B, with CE(A, h) − CE$(B, h) = 500$. The estimates of λ_h imply that 22% of married couples will select the lower value plan compared to 16% of widows, 14% of widowers and 10% of divorced women.

The second row of the table shows the money metric estimates for status quo inertia. The magnitude of the estimates for single households is similar to previous studies by Handel (2013), Polyakova (2016), and Ketcham, Kuminoff and Powers (2019). The estimate for married couples is \$3,152, two times the estimate for divorced women. Note that on one hand, couples face a harder problem, in the sense that they have to choose from a menu with more options. If each spouse chooses among 50 plans, couples have to decide among 50 by 50 plan combinations. On the other hand, couples can exploit information economies of scale, (Wilson, 1975) or help each other in the search process. Interestingly, my estimates of inertia for couples are similar to Handel's (2013) largest estimates for families in markets for employer-sponsored health insurance plans (\$3,006). This is somewhat surprising, because married couples in Part D have to choose two plans among 50^2 options, whereas families in his setting choose a single plan among 5 options.

Interestingly, the difference between widows and divorced women is quite large. The difference is approximately equal to the average (subsidized) annual premiums in Part D, \$500. Recall that these measures are expressed in terms of certainty equivalents so they should be interpreted from an ex-ante perspective. For example, suppose that a widow has to choose between a gamble and a riskless position. If she chooses the gamble she can lose 5,000 dollars with probability p and zero with complementary probability. In the riskless position, she loses zero dollars with certainty. The estimated status quo inertia, \$1,975, implies that a widow with average risk aversion will be indifferent between taking the gamble and maintaining a riskless position when $p = 0.35$.[27] This means that plans have to get significantly worse in terms of coverage in order to induce widows to switch to another alternative. The reason why status quo bias is higher among the set of widows is simple. Widows are the most risk averse agents in the market (because they tend to be older then divorced women and have higher medical spending), so they are the ones who stand to gain the most by switching. The fact that they switch at the same rate ass less risk averse agents, 10%, can only be rationalized with higher status quo inertia.

The coefficient on "couple last year" measures status quo inertia for widowed

[27]The average absolute risk aversion for widows is 0.00007.

people who were married in the previous year to test whether death of a spouse may reduce inertia. The estimates are not different from enrollees who were already widowed last year, suggesting that death of a spouse does not reduce inertia, at least in the short term.

The third row of the table reports a money metric for couples' implied willingness to pool, Ω. Interestingly, Ω is approximately half the size of K, ($1,584). The revealed preference logic of the maximum likelihood estimator requires Ω to be smaller than K to rationalize the fact that most couples decide to buy the same plan.

Returning to the coefficients on "couple last year", notice that the estimates conflate the effects of two changes: a year-to-year change in plan menu, and, a change in the preference function of households who were previously choosing plans jointly with their spouse. When compared with the choice of an active widower, both effects must be taken into account. I can not disentangle these two effects because there is no region where plans menus were unchanged from one year to the next between 2006 and 2010. The estimates for men and women are similar to enrollees who were already widowed last year.

Comparing these measures for inertia between couples and singles is consistent with the hypothesis that one member of the couple is in charge of selecting both plans. Under this hypothesis, the estimates for couples should be double the estimates for singles. Another observationally equivalent hypothesis is that both spouses choose their own plans with complete autonomy. However, this second hypothesis seems less likely to drive behavior because it does not seem capable of explaining the high rate of pooling.

6 Policy Analysis

The policy counterfactuals envision a regulator who will nudge consumers to conform with expected utility. The counterfactual scenarios simulate how premiums will respond to changes in the way that consumers sort themselves across plans as a consequence of the policy. Section 6.1 describes the institutional details of how premiums and plan payments are set in Part D. Section 6.2 defines "nudge" in the context of my stochastic choice model. Section 6.3 describes the policy counterfactuals. Finally, section 6.4 summarizes results.

6.1 Insurance Payments and Premium Subsidies

As noted earlier, plan payments in Medicare Part D are risk adjusted. This means that plan providers are compensated with payments that vary with the chronic condition of their pool. For example, the risk adjustment payment that a plan provider receives for insuring individual i is:

$$\sum_{cc} W_{cc} D_{icc} \,, \tag{9}$$

where W_{cc} is the risk adjustment payment for chronic condition cc and D_{icc} is a dummy variable equal to one if individual i has chronic condition cc. In the same fashion, the plan receives a demographic risk adjustment component depending on the demographic characteristics d of individual i, $\sum_d W_{cc} D_{id}$.[28] W_{cc} and W_d are measured in dollars and the risk score described in previous sections results from the following formula:

$$\text{risk score}_i = \frac{\sum_x W_x D_{ix}}{\sum_x W_x D_{\bar{i}x}} \,, \tag{10}$$

where $\bar{i}$ represents the average enrollee and x includes the chronic conditions and demographic risk adjusters. It is clear from equation 10 that enrollees sicker than average will have a risk score greater than one, while enrollees who are healthier than average will have a risk score less than one.

I assume that insurance companies are risk neutral and that the market is competitive. Therefore, each plan must make zero profits in equilibrium. In competitive markets with no risk adjustment plan bids will reflect average costs of each plan. In this scenario, differences in plan bids reflect differences in average costs across plans:

$$bid_j = E(\text{cost}_j) \tag{11}$$

[28] See Carey (2017) for a more comprehensive treatment of risk adjustment payments in Medicare Part D.

In contrast, with partial risk adjustment plan bids are defined by the following equation:

$$bid_j = E(\text{cost}_j) - E(\text{RA}_j) + E(\text{cost}) \tag{12}$$

Now differences in plan bids reflect differences in average residual costs, (Layton, 2017). The residual cost of individual i is the difference between total cost and his risk adjusted payments; in other words, costs that can not be predicted by the model. Note that if risk adjustment was perfect, then insurance companies would be bidding the average cost of the market and there would be no difference in plan bids.

Following the actuarial literature I assume that firms form expectations of future costs (residual costs) with the average cost (residual cost) of enrollees that are currently under the plan.[29] This stylized model of plan pricing attempts to capture the key features of how insurance companies set their bids in this market. In the bidding process, insurance companies have to send a bid that represents the estimated cost for providing the basic benefit. Bids for the upcoming year are submitted in the current year. Given the timing of this process, the bid will likely carry information on the current pool of enrollees in each plan.

Plan premiums in Part D are defined by the following equation:

$$\text{premium}_j = \text{bid}_j - \theta\text{NAB} \tag{13}$$

This means that enrolleess pay the difference between the plan bid and the national average bid (NAB) multiplied by a factor of θ.[30] This last parameter represents the share of premiums that are subsidized by the government. The counterfactual scenario without plan subsidies corresponds to $\theta = 0$:

[29] This backward looking depiction of firm behavior is motivated by the empirical presence of adverse selection "death spirals" in insurance markets, (Cutler and Reber, 1998; Handel, 2013).

[30] θ is on average 75% in the first five years of the program.

$$\text{premium}_j = \text{bid}_j \tag{14}$$

In summary, policymakers can adjust the level of government involvement in the market through the risk adjustment formula and through the subsidy level. Table 10 summarizes alternative market environments with and without each of these features.

Table 10: Policy Environments

	Subsidy		No Subsidy	
	Payments	Premiums	Payments	Premiums
Risk Adjustment	(Eq. 12	Eq. 13)	(Eq. 12	Eq. 14)
No Risk Adjustment	(Eq. 11	Eq. 13)	(Eq. 11	Eq. 14)

Notes: Table 10 depicts four types of environments depending on the presence or not of risk adjustment payments and premium subsidies. Plan premiums and plan payments can be represented by any combination of equations 11-14. The current environment of Medicare Part D is represented by the combination of equation 12 and 13.

I analyze how these four environments affect the relative costs of couples and singles when the government nudges them to adjust their choices. The exercise is meant to provide insight on how couples' behavior would be likely to affect adverse selection in markets with different regulations, including but not limited to the current environment of Part D.

6.2 Nudges

The policy counterfactuals envision a regulator who will nudge consumers to conform with expected utility, his preferred normative theory. The regulator, faces a trade-off. The nudge will create an incentive for consumers to choose higher value plans. At the same time, because risk is not fully priced, consumer sorting may increase adverse selection, (Akerlof, 1970; Rothschild and Stiglitz, 1976). This trade-off is studied in the health insurance context by Handel (2013) and by Polyakova (2016). My analysis extends this literature by investigating how this trade-off is modified by consumer demographics, specifically, how the interactions within couples and the interaction between couples and widows.

Like prior studies, I assume that the policy affects household choices by reducing λ_h in some percentage κ. However, unlike most prior studies, I recognize that the policy may affect different household types differently. For example, prior studies have proposed nudging seniors to use the Medicare Part D Plan Finder tool, (Kling et al., 2012). Plan Finder is meant to be a friendly platform on Medicare.gov that allows seniors to compare plans in Part D or Medicare Advantage. Married couples and widows may react quite differently to such a policy. Widows tend to belong to older cohorts who are less likely to use a computer and the internet as shown by the following table.

Table 11: Question on Internet Use MCBS

Do you personally ever use the Internet to get information of any kind?	yes	no
Spouses	46	54
Widows	21	77

Notes: Table 11 is based on a question asked on the Medicare Current Beneficiary Survey between years 2006-2010. The table shows the average share of seniors by answer across this sample period.

Table 11 is derived from Medicare Current Beneficiary Survey and suggests that widows will be less likely to use the internet to compare plans. This example is simply meant to motivate the exercise that I am interested in exploring: the welfare consequences of nudging heterogeneous consumers such as couples and widows who are likely to respond differently to the policy.[31]

I simulate market adjustment in scenarios where couples and widows are affected differently by the policy with a wedge $w = \kappa_c - \kappa_w$, where κ_c and κ_w are the fractions by which λ_c and λ_w are reduced as a result of the policy. Since the level of w would be policy-specific, I bound welfare for different levels of w. Throughout

[31] Although in the example I am suggesting that widows could be less affected by the policy, we could imagine policies where the opposite happens. For example, widows will be likely more affected than couples with a policy that automatically enrolls seniors in a default plan. In general, more information will be needed to assess the plans that best meets the needs of a couple than for one single person. I show the results of a policy with this feature in Appendix B.

the simulations, I set κ_w to 0.9, a 10% reduction, and report the welfare implications and outcomes for differently sized wedges w.

The error terms that define deviations from expected utility in the stochastic choice model are assumed to be irrelevant for calculating consumer welfare. Of course, the errors may also reflect sources of unobserved heterogeneity that affect the willingness to pay for insurance such as the quality of customer service or pharmacy networks.[32] Thus, my simulation exercises assume that the policy targets the component of the error that is not explained by unobserved heterogeneity.

6.3 Policy Counterfactual

I simulate the effects of nudges in four counterfactual environments.

Counterfactual I: This scenario considers policy that reduces λ_w, the scale parameter of widows, by 10% and at the same time reduces the scale parameter of couples by different magnitudes. The policy is modeled as starting in 2007 and continuing through 2010. Importantly, I conduct this experiment in a market without premium subsidies and risk adjustment payments. Therefore, bids and premiums will be determined by equations11 and 14.

Counterfactual II: This scenario is the same as counterfactual I but adds risk adjustment payments. This experiment is meant to reveal how risk adjustment payments influence the sorting patterns of couples and singles in response to a nudge. Thus, bids will be determined by equation 12 and premiums by equation 14.

Counterfactual III: This scenario is the same as counterfactual II but adds subsidies to mirror the real Part D environment. The subsidies will obviously limit adverse selection and improve consumer welfare. The question is by how much. Here bids and premiums will be determined by equations 12 and 13.

Taken together, the first three counterfactuals will allow me to determine how each feature of this market affects outcomes when considering policies that nudge consumers toward different choices. This knowledge is important for assessing the implications of similar policies that could be introduced in markets that do not share

[32] In one extreme, one could interpret ϵ as completely driven by unobserved heterogeneity, (Bundorf, Levin and Mahoney, 2012) and in the other extreme we can interpret ϵ as completely driven by errors, (Abaluck and Gruber, 2011).

the same regulations as Part D, such as the Medicare Advantage markets where plan premiums are not as heavily subsidized.

Counterfactual IV: The final counterfactual is a thought experiment in which I compare the evolution of the market with risk adjustment payments from counterfactual II with two models. The first model corresponds to my estimation results where spouses choose plans as a group and share risks. The second model treats each spouse separately. When they decide in isolation, each spouse will make a choice with their own risk aversion parameter σ_i and when they decide as a couple they will still do it with σ_i^*. The comparison of both models will shed light on how couples' behavior affects outcomes in individual insurance markets.

Simulation mechanics: Each simulation consists of solving for market outcomes with the estimated model. I simulate the baseline and each counterfactual 500 times and report average outcomes. The policy consists of reducing λ_h from 2007 onward. In each replication a baseline scenario with an initial allocation of consumers is compared to the policy scenario. I am interested in isolating the effect of different households responding differently to the designed policy. Welfare will be measured with the certainty equivalent money metrics. Therefore, the comparison of scenario A with scenario B for household i will be done with the money equivalent $me_i = \text{CE}_i(A) - \text{CE}_i(B)$.[33]

6.4 Results

Tables 12, 13 and 15 summarize results from the first three counterfactuals. In each table, the first four rows show the changes in the welfare of couples in years 2007-2010. The next four rows shows the changes in the welfare for singles. "Share Pooling" shows the share of couples who still decide to pool after the policy. The next three rows show the average increase in premiums in the last three years of the policy relative to the baseline scenario. The last two rows shows the share of plans that suffer adverse selection death spirals in each scenario. I define a death spiral as a situation where the plan share decreases every year and premiums increase every year. This patterns implies that enrollees who exit the plan are relatively

[33]See Pope and Chavas (1985) for a comparison of this metric with other welfare measures under uncertainty.

healthier than enrollees who stay. The variation in premiums and the death spiral count provide two quantitative measures for the degree of adverse selection.

Table 12 summarizes counterfactual I. Each column reports results for a different wedge: $w = 0$ means that the policy reduces λ_c by 10%, $w = 0.1$ is the situation where the policy reduces λ_c by 20%, and so on. The welfare and premium changes are always calculated relative to the baseline scenario where enrollees are not nudged. Couples' welfare increases after nudging enrollees. The welfare of singles decreases slightly. The nudge tends to induce couples to move to plans with smaller shares of widows. Since couples' risk premium is small relative to widows, they are not willing to pay plan premiums that do not reflect their own costs. At the same time, this sorting behavior makes widows pay higher premiums in subsequent years relative to the baseline scenario.

After the policy, 90% of couples still decide to pool on average. This increase in pooling is mainly driven by the fact that 36% of plans suffer from death spirals. Thus, there are fewer plans to choose from. This fact and the average increase in premiums relative to the baseline reveals that most plans get adversely selected after the policy.

Note that both types of heterogeneity are important for the results. If couples were similar to widows in terms of cost, the fact that they have different preferences will not be sufficient to generate the results because their movement to other plans would not lead to large changes in premiums. At the same time, if couples differed in terms of costs, but had the same preferences with widows, then they would be likely to buy the same plans, subsidizing widows and preventing plans with higher shares of widows from suffering death spirals. In summary, couples' increase in welfare comes at the cost of a slightly decrease in welfare for widows.

Table 12: Counterfactual I. No Risk Adjustment - No Subsidies

mean welfare change couples (%)	w=0	w=0.1	w=0.2	w=0.3	w=0.4
2007	0%	1%	2%	4%	7%
2008	-1%	1%	3%	8%	13%
2009	0%	1%	3%	10%	13%
2010	2%	-1%	1%	4%	13%
mean welfare change singles (%)					
2007	0%	0%	0%	0%	0%
2008	-1%	0%	0%	0%	0%
2009	-3%	-3%	-4%	-3%	-3%
2010	-4%	-4%	-3%	-3%	-3%
Share Pooling - Policy	86%	87%	90%	90%	91%
premium variation					
2008	10%	9%	8%	6%	6%
2009	20%	20%	19%	17%	18%
2010	11%	13%	11%	13%	11%
(%) Death Spirals - Baseline	29%	32%	32%	29%	32%
(%) Death Spirals - After Policy	32%	32%	36%	36%	36%

Notes: Table 12 shows the results from counterfactual I. The environment consists of a market without risk adjustment and without premium subsidies. κ_w is set to 0.9 in 2007 onward, a 10% decrease in λ_w. Each columns shows the results of the policy for different wedges. $w = 0$ corresponds to the scenario where couples are equally affected by the policy. $w = 0.1$ corresponds to the scenario where $\lambda_c = 0.8$, and so on. The first rows of the table report the welfare change for couples and singles after the policy. "Share Pooling" shows the share of couples who still decide to pool after the policy. The premiums variation shows the average increase in premiums relative to the baseline scenario in the last three years of the policy. The last two rows show the share of plans that suffer adverse selection death spirals.

Table 13: Counterfactual II. Risk Adjustment - No Subsidies

mean welfare change couples (%)	w=0	w=0.1	w=0.2	w=0.3	w=0.4
2007	0%	1%	3%	6%	11%
2008	-3%	1%	6%	14%	26%
2009	2%	9%	19%	36%	48%
2010	0%	-1%	2%	2%	9%
mean welfare change singles (%)					
2007	0%	0%	0%	0%	0%
2008	-2%	-2%	-2%	-2%	0%
2009	-9%	-6%	-8%	-7%	-7%
2010	-7%	-8%	-8%	-8%	-9%
Share Pooling - Policy	90%	90%	91%	91%	95%
premium variation					
2008	17%	16%	13%	13%	10%
2009	10%	8%	13%	11%	14%
2010	16%	13%	22%	23%	22%
(%) Death Spirals - Baseline	32%	32%	29%	32%	29%
(%) Death Spirals - Policy	32%	32%	36%	36%	36%

Notes: Table 13 shows the results from counterfactual II. The environment consists of a market with risk adjustment payments and without premium subsidies. κ_w is set to 0.9 in 2007 onward, a 10% decrease in λ_w. Each columns shows the results of the policy for different wedges. $w = 0$ corresponds to the scenario where couples are equally affected by the policy. $w = 0.1$ corresponds to the scenario where $\lambda_c = 0.8$, and so on. The first rows of the table report the welfare change for couples and singles after the policy. "Share Pooling" shows the share of couples who still decide to pool after the policy. The premiums variation shows the average increase in premiums relative to the baseline scenario in the last three years of the policy. The last two rows show the share of plans that suffer adverse selection death spirals.

Table 13 summarizes how adding risk adjustment payments to the environment changes outcomes. Recall from section 3 that risk adjustment makes widows a riskier proposition for insurance companies relative to couples. Therefore, when couples move away from plans with high shares of widows, premiums adjust more relative to an environment without risk adjustment. This implies that couples' welfare will increase more relative to the environment without risk adjustment and widows will be worse off, and Table 13 confirms these predictions. Imperfect risk adjustment, increases the effects of the nudge. The welfare increase among couples is considerably higher than in an environment without risk adjustment. In the best year, this policy is able to generate a increase in welfare of 48% for couples, while in the previous environment the welfare increased by 13% in the best year. As expected, the increase in premiums is higher relative to the environment without risk adjustment, which makes singles relatively worse off.

These results beg the question of whether there is information content in the marital status of enrollees that could usefully be taken into account in the risk-adjustment model. Table 14 explores this idea by comparing the difference in costs and residual costs of widows and divorced women relative to couples. The last row shows the increase in the difference between average cost and residual costs relative to married couples. When we compare couples with divorced women, there is little difference in average costs. On average, divorced women are 68 dollars more expensive than couples. The difference in residual costs however increases by almost 150%. Interestingly, the risk adjusted model generates less distortion between the costs of widows and divorced women. The difference in residual costs in roughy 15% less than the difference in average cost.[34] The table suggests that there are factors that make couples' true costs more similar than singles' that the risk adjustment model is not able to capture. This could include behavioral factors as suggested by Einav et al. (2016) or factors that can influence health beyond chronic conditions. Thus, the inclusion of marital status in the risk score could reduce the gap between residual costs among households and mitigate adverse selection.

[34]This calculation follows from the difference in average costs of widows and divorced women (1,116-923=193), with the difference in residual costs of these households (453-289=164).

Table 14: Costs and Residual Costs Relative to Couples

	Widow	Difference with couple	Divorced Women	Difference with couple
Average Cost	1,116	260	923	68
Average Residual Cost	453	332	289	168
Variation		28%		148%

Notes: Table 14 shows the average cost and residual cost for widows and divorced women. It also shows for each of these two variables the difference with married couples. The last row shows the increase in the difference between average cost and residual costs relative to married couples.

Table 15 shows the results from implementing the nudge in the actual Part D environment, with risk adjustment payments and premium subsidies. The subsidy is the primary factor that limits adverse selection after we nudge enrollees. Both household types are made better off by the policy. Premiums decrease on average and the share of plans that suffer from death spirals is reduced to 20% on average. These results are broadly consistent with Polyakova's (2016) findings. In her setting, all enrollees are assumed to be equally affected by the policy. This exercise shows that the presence of the subsidy is the main reason why nudging can be successful from the policymaker's perspective. This is important because in markets that are not as heavily subsidized as Part D, the effects of the policy will be likely to work in the opposite direction as shown in the first two counterfactuals.

Table 15: Counterfactual III. Risk Adjustment - Subsidies

mean welfare change couples (%)	w=0	w=0.1	w=0.2	w=0.3	w=0.4
2007	0%	1%	4%	7%	12%
2008	-3%	4%	12%	23%	36%
2009	24%	33%	52%	59%	80%
2010	-1%	-1%	1%	3%	14%
mean welfare change singles (%)					
2007	-1%	-1%	-1%	0%	0%
2008	0%	2%	4%	1%	2%
2009	18%	20%	9%	13%	14%
2010	3%	2%	2%	2%	3%
Share Pooling - Policy	90%	90%	90%	93%	95%
premium variation					
2008	-24%	-14%	-12%	-13%	-8%
2009	-26%	-36%	-40%	-38%	-39%
2010	-44%	-38%	-42%	-41%	-45%
(%) Death Spirals - Baseline	21%	21%	18%	18%	21%
(%) Death Spirals - Policy	21%	21%	21%	25%	25%

Notes: Table 15 shows the results from counterfactual III. The environment consists of a market without risk adjustment and with premium subsidies. κ_w is set to 0.9 in 2007 onward, a 10% decrease in λ_w. Each columns shows the results of the policy for different wedges. $w = 0$ corresponds to the scenario where couples are equally affected by the policy. $w = 0.1$ corresponds to the scenario where $\lambda_c = 0.8$, and so on. The first rows of the table report the welfare change for couples and singles after the policy. "Share Pooling" shows the share of couples who still decide to pool after the policy. The premiums variation shows the average increase in premiums relative to the baseline scenario in the last three years of the policy. The last two rows show the share of plans that suffer adverse selection death spirals.

In summary, combining my results with finding from prior studies suggest that a policy that helps consumers make more informed choices has potential to be successful in the current Medicare Part D environment even after accounting for adverse selection. The fact that the subsidy is able to overcome the positive correlation between prescription drug expenditure and risk aversion together with the distortion in costs generated by the risk adjustment model speaks about the important role of premiums subsidies in the functioning of this market.

Finally, Table 16 summarizes results from Counterfactual IV where I compare the effects of the policy with and without accounting for the way that couples interact in their decision-making. The nudge in this case is one where singles are not affected at all and couples λ_h is reduced by 50%. This setup makes the results in the first column comparable to the last columns of table 13 where the wedge between couples and singles was 0.4. The second column shows results when spouses are treated separately, and assumed to make separate decisions based on their individual levels of risk aversion.

Model predictions are very different. In the scenario where spouses are choosing individual insurance plans on their own, single individuals are hurt less. The reason is simple: when spouses are not able to share risk, they are more risk averse than when they choose as a couple. This increase in risk premium of each spouse makes them more prone to select the same plans as widows. Therefore, widows do not experience an increase in premiums relative to the scenario where spouses shop together. The welfare of spouses increases moderately because although they are able to find plans of higher value (as individuals) they also pay a higher premium since they tend to pool with widows. Spouses' preferences are now more aligned with the preferences of widows, in particular the preference of wives who are generally predicted to be more risk averse than husbands. Interestingly, only 4% of couples decide to buy the same plan after the policy, had they chosen plans in isolation compared to 95% when they shop as couples. Hence, independent decision-making would almost completely eliminate within-household pooling.

Table 16: Counterfactual IV. Ignoring Within-Household Coordination

mean welfare change couples (%)	risk sharing	no risk sharing
2007	11%	3%
2008	28%	3%
2009	50%	2%
2010	11%	0%
mean welfare change singles (%)		
2007	0%	0%
2008	-1%	-2%
2009	-8%	0%
2010	-7%	-1%
Share Pooling	95%	4%
premium variation		
2008	10%	2%
2009	8%	4%
2010	18%	4%
(%) Death Spirals - Baseline	32%	0%
(%) Death Spirals - Policy	36%	0%

Notes: Table 16 shows the results from counterfactual IV. The environment consists of a market with risk adjustment and without premium subsidies. κ_w is not affected by the policy. λ_c is reduced by 50%. The first column shows the results with the model where spouses decide as a group. The second column shows the results with the model where spouses decide separately. The first rows of the table report the welfare change for couples and singles after the policy. "Share Pooling" shows the share of couples who still decide to pool after the policy. The premiums variation shows the average increase in premiums relative to the baseline scenario in the last three years of the policy. The last two rows show the share of plans that suffer adverse selection death spirals.

This example shows that joint decision-making is important for predicting how markets response to a nudge, and the welfare implications involved. Although couples represent more than half of the market, the fact that they choose plans together reduces their willingness to pay for plans with higher coverage, which are the plans preferred by most widows. The premium subsidy is replacing the cross subsidization that could have emerged endogenously had the spouses chosen plans separately.

Overall, the four counterfactuals examined in this section reveal how different features of this market interact with policies that nudge consumers to shape market outcomes and their welfare implications. The heterogeneity in costs and preferences of the main two consumer groups exacerbates adverse selection after the policy. Risk adjustment increases the differences in costs of couples and widows. This increases the distributional welfare consequences of the policy and it exacerbates adverse selection. The federal subsidy is the key feature of the market that allows the nudge to achieve the policymaker's objective. It increases the likelihood that couples and widows choose the same plans and therefore mitigates adverse selection. An implication of these findings is that markets that are not as heavily subsidized as Part D, are likely to have greater disparities between winners and losers from policies that help consumers make more informed choices.

7 Conclusion

In recent years much attention has been devoted to understanding the equity and efficiency of federally regulated health insurance markets in the US. From understanding the choices of consumers to the incentives of firms, the emergence of these markets sparked many studies that advanced knowledge of the economics of regulated health insurance markets and their policy implications. However, the entire literature to date has focused on modeling individual choices. The fact that most federally regulated health insurance markets (Part D, Medigap, Advantage) only sell individual plans does not imply that consumers will choose plans as individuals. A large proportion of consumers in these markets are married and married couples have strong incentives to coordinate on their enrollment choices.

This paper is the first economic study to analyze the behavior of married couples in individual health insurance markets. It sheds light on how their behavior and interactions with other types of households affects market functioning. I documented that, strikingly, more than two thirds of couples decide to buy the same plan, that their degree of positive assortative mating in expenditure risk is small compared to other contexts such as education, and that their degree of inertia is similar to singles. However, I also found that couples differ from singles in terms of risk aversion and costs. Spouses are in general less costly to insurance companies compared to other types of households (widowed, divorced, etc) and less risk averse. These differences are crucial to understanding the consequences of policies that nudge consumers toward different choices. The fact that couples behave less risk adversely than single households because they are able to share risks makes it harder to contain adverse selection when consumers are nudged toward enrolling in higher-value plans.

I also characterized how standard regulatory features of insurance markets like risk adjustment payments and premium subsidies modify the ways in which different types of households sort themselves across the market in response to a nudge. In Medicare Part D, the imperfect risk adjustment model makes single households more costly relative to couples, exacerbating adverse selection. The inclusion of marital status as a risk adjustment component would likely moderate some of the distortions. Finally, my results suggest that premium subsidies are essential for nudges to be broadly welfare improving in the Part D context.

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Appendix A

The procedure to estimate the gaussian copula is described in this section. With the empirical analog of the marginal distribution of each spouse $u_i = F_i(x)$ already estimated. I construct the distribution of $z = x_1 + x_2$, with x_i denoting the out of pocket cost of each spouse, with the following three-step process:

1. Draw random variables $[V_1 \;\; V_2] \sim N([0 \;\; 0], [1 \;\; \rho \;\; \rho \;\; 1])$, for a given parameter ρ.

2. Construct a pair of uniform random variables $U = [\Phi(V_1) \;\; \Phi(V_2)]$.

3. Generate $[X_1 \;\; X_2] = [\hat{F_1}^{-1}(U_1) \;\; \hat{F_2}^{-1}(U_2)]$, where $\hat{F_i}^{-1}$ is the inverse of the empirical cdfs of each spouse's marginal distribution.

Under this formulation, the only parameter to be estimated is ρ. For tractability, I assume that ρ is constant across diseases. Under the gaussian copula form, ρ has the following relation to Spearman's rank correlation coefficient τ, (Trivedi and Zimmer, 2006):

$$\rho = 2\text{sin}\left(\frac{\pi}{6}\tau\right) \tag{15}$$

Therefore, any consistent estimator of τ, $\hat{\tau}$, will make the plug-in estimator $\hat{\rho} = 2\text{sin}(\frac{\pi}{6}\hat{\tau})$ a consistent estimator of ρ. Using this formula, I estimated $\hat{\rho}$ to be equal to 0.3 (p=0.0000). This means that couples risk exhibits a positive dependence, consistent with the intuition for broken heart syndrome.

Appendix B

This section shows the results of a policy where widows' decision-errors are more affected relative to couples. I report results for the first three counterfactuals summarized in section 6. The results of the first two counterfactuals are similar to the case where spouses react more to the policy but with opposite effects. Interestingly, however, in the actual setting of Medicare Part D couples' welfare only increases in one year after the nudge (2009). The subsidy is less effective in a scenario where widows, the worst risk of the market, react more to the policy than spouses.

Table B1: Counterfactual I. No Risk Adjustment - No Subsidies

mean welfare change couples (%)	w=0	w=0.1	w=0.2	w=0.3	w=0.4
2007	0%	0%	0%	0%	0%
2008	-1%	0%	-1%	0%	-1%
2009	0%	0%	0%	0%	0%
2010	-1%	-1%	0%	-1%	-1%
mean welfare change singles (%)					
2007	0%	0%	0%	1%	2%
2008	-1%	0%	2%	4%	7%
2009	-3%	-1%	1%	4%	7%
2010	-4%	-3%	-3%	-3%	0%
Share Pooling - Policy	86%	86%	85%	86%	86%
premium variation					
2008	9%	10%	9%	9%	10%
2009	20%	19%	21%	20%	21%
2010	10%	13%	12%	13%	14%
(%) Death Spirals - Baseline	32%	32%	32%	32%	32%
(%) Death Spirals - After Policy	32%	32%	36%	36%	39%

Notes: Table B1 shows the results from counterfactual III. The environment consists of a market without risk adjustment and with premium subsidies. κ_c is set to 0.9 in 2007 onward, a 10% decrease in λ_c. Each columns shows the results of the policy for different wedges. $w = 0$ corresponds to the scenario where widows are equally affected by the policy. $w = 0.1$ corresponds to the scenario where $\lambda_w = 0.8$, and so on. The first rows of the table report the welfare change for couples and singles after the policy. "Share Pooling" shows the share of couples who still decide to pool after the policy. The premiums variation shows the average increase in premiums relative to the baseline scenario in the last three years of the policy. The last two rows show the share of plans that suffer adverse selection death spirals.

Table B2: Counterfactual II. Risk Adjustment - No Subsidies

mean welfare change couples (%)	w=0	w=0.1	w=0.2	w=0.3	w=0.4
2007	0%	0%	0%	0%	0%
2008	-2%	-2%	-2%	-1%	-4%
2009	3%	1%	2%	3%	-3%
2010	0%	0%	0%	-1%	-1%
mean welfare change singles (%)					
2007	0%	0%	1%	2%	4%
2008	-2%	1%	3%	7%	12%
2009	-11%	-6%	3%	9%	19%
2010	-7%	-8%	-7%	-6%	-5%
Share Pooling - Policy	90%	89%	90%	90%	89%
premium variation					
2008	17%	15%	16%	18%	19%
2009	17%	6%	10%	11%	12%
2010	17%	21%	23%	22%	23%
(%) Death Spirals - Baseline	32%	32%	32%	29%	29%
(%) Death Spirals - Policy	32%	32%	36%	36%	39%

Notes: Table B2 shows the results from counterfactual III. The environment consists of a market without risk adjustment and with premium subsidies. κ_c is set to 0.9 in 2007 onward, a 10% decrease in λ_c. Each columns shows the results of the policy for different wedges. $w = 0$ corresponds to the scenario where widows are equally affected by the policy. $w = 0.1$ corresponds to the scenario where $\lambda_w = 0.8$, and so on. The first rows of the table report the welfare change for couples and singles after the policy. "Share Pooling" shows the share of couples who still decide to pool after the policy. The premiums variation shows the average increase in premiums relative to the baseline scenario in the last three years of the policy. The last two rows show the share of plans that suffer adverse selection death spirals.

Table B3: Counterfactual III. Risk Adjustment - Subsidies

mean welfare change couples (%)	w=0	w=0.1	w=0.2	w=0.3	w=0.4
2007	-1%	-1%	-1%	0%	-1%
2008	-2%	-5%	-5%	-4%	-2%
2009	23%	27%	22%	13%	18%
2010	0%	1%	-5%	-4%	-5%
mean welfare change singles (%)					
2007	-1%	0%	1%	3%	6%
2008	-1%	4%	9%	17%	24%
2009	6%	19%	24%	36%	41%
2010	2%	3%	2%	3%	5%
Share Pooling - Policy	90%	90%	90%	90%	90%
premium variation					
2008	-8%	-15%	-17%	-15%	-12%
2009	-43%	-37%	-37%	-37%	-54%
2010	-38%	-47%	-41%	-45%	-43%
(%) Death Spirals - Baseline	21%	21%	18%	21%	21%
(%) Death Spirals - Policy	21%	21%	25%	25%	29%

Notes: Table B3 shows the results from counterfactual III. The environment consists of a market without risk adjustment and with premium subsidies. κ_c is set to 0.9 in 2007 onward, a 10% decrease in λ_c. Each columns shows the results of the policy for different wedges. $w = 0$ corresponds to the scenario where widows are equally affected by the policy. $w = 0.1$ corresponds to the scenario where $\lambda_w = 0.8$, and so on. The first rows of the table report the welfare change for couples and singles after the policy. "Share Pooling" shows the share of couples who still decide to pool after the policy. The premiums variation shows the average increase in premiums relative to the baseline scenario in the last three years of the policy. The last two rows show the share of plans that suffer adverse selection death spirals.