Appendix A: A Simulation Exercise

In this section we demonstrate that the choice restrictions we test in our conditional logit model would be satisfied by a broad range of generalized utility functions. We start by considering CARA and CRRA utility functions with a range of values for risk aversion. We then take the cost distributions generated from the Part D data for each plan and simulate individuals' choices using the assumed utility function. Finally, we estimate the conditional logit model using these simulated choices and check whether the restrictions considered above hold. We add a small amount of noise to each observation so that the coefficients are identified at small levels of risk aversion.[23] The results of this exercise are reported in Appendix Table 1.

The CRRA utility function is evaluated at wealth $17,000, the median financial wealth of those age 65-74 in 2004 (EBRI, 2005). This is a conservative assumption which will tend to increase the curvature – and thus the degree of misspecification (it is especially conservative given that our analysis excludes individuals eligible for low-income subsidies). The absolute magnitude of the coefficients is determined by the amount of added noise (since this is the only omitted factor). A more informative measure is the size of each coefficient relative to the coefficient on premiums: this measure gives the dollar value of a one unit change in the included variable.

Regarding the first restriction, we see that, provided risk aversion is not too large (CRRA < 3, CARA < .0001), the coefficient on premiums equals the coefficient on OOP costs, and the two are very comparable in magnitude even at more extreme levels of risk aversion. The second restriction appears to hold roughly over the same range: the plan characteristics are insignificant controlling for the mean and variance of out of pocket

[23] The standard deviation of the noise to 1/20th of the interquartile range of utility.

costs provided CRRA < 3 and CARA < .003. Even in the cases when they are significant, they are small in magnitude relative to premiums. Dividing the coefficient on each variable by the coefficient on premiums gives the dollar value of a 1 unit increase in the variable. In the CRRA = 10 case, the results would imply that individuals are willing to pay $9 for (full) donut hole coverage, would have to be paid $33 to go from a 0 deductible to a $250 deductible, and would have to be paid $8 to accept generic donut hole coverage (since these values are driven entirely by misspecification there is no reason the signs should be sensible). The third restriction is satisfied in the sense that we estimate risk aversion in all cases when the coefficient of risk aversion is greater than 0. The “risk index” is obtained by dividing two times the coefficient on the variance term by the coefficient on premiums. We showed above that with CARA utility and normal noise, this index should approximate to (10^6 times) the coefficient of absolute risk aversion. We see in Appendix Table 1 that this approximation seems to get things roughly correct in our sample (despite the fact that costs are non-normal), although it begins to break down when risk aversion is grows very large.

Appendix Table 1: Simulation Results

	CRRA (wealth = 17000)			CARA		
	1	**3**	**10**	**0.0001**	**0.0003**	**0.0005**
Premium	-5.385**	-5.057**	-3.407**	-5.288**	-4.774**	-3.877**
(hundreds)	(.0364)	(.0337)	(.0199)	(.0354)	(.0312)	(.0237)
OOP Cost	-5.355**	-4.911**	-2.767**	-5.284**	-4.517**	-3.379**
(hundreds)	(.0369)	(.0335)	(.0237)	(.0359)	(.0324)	(.0268)
Variance	-1.903**	-6.293**	-19.87**	-2.600**	-9.244**	-16.28**
(times 10^6)	(.1536)	(.1329)	(.1985)	(.1489)	(.1436)	(.1919)
Deductible	-.0409	-.1567**	-.4452**	-.0424	-.2177**	-.3728**
(hundreds)	(.0225)	(.0211)	(.0188)	(.0221)	(.0211)	(.0198)
Donut Hole	-.0390	-.2506**	.2974**	.0210	-.0254	-.2393**
	(.0863)	(.0781)	(.0549)	(.0657)	(.0703)	(.0626)
Generic Donut Hole	-.0470	-.1412*	-.2829**	-.0325	-.1326**	-.2782**
	(.0680)	(.0652)	(.0560)	(.0657)	(.0629)	(.0571)
Cost Sharing	.1905	1.207**	2.791**	.2915	1.672**	2.726**
	(.2546)	(.2425)	(.2114)	(.2505)	(.2393)	(.2230)
# in Top 100	.0115	-.0045	-.0056**	.0110	-.0121**	-.0098**
	(.0036)	(.0031)	(.0023)	(.0036)	(.0029)	(.0024)
Avg. Quality Rating	-.1281	-.0508	.0525**	-.1186	-.0082	.0349**
	(.0181)	(.0164)	(.0128)	(.0175)	(.0155)	(.0137)
Risk Index	71	249	1166	98	387	840
# of patients	94732	94732	94732	94732	94732	94732
# of plans	702	702	702	702	702	702
# of states	47	47	47	47	47	47
# of brands	36	36	36	36	36	36

Notes: Table shows conditional logit results from estimating the model given in equation (6) by maximum likelihood using simulated choices. Each column shows coefficients from a single regression. The coefficients reported are the parameters of the utility function, not marginal effects. Standard errors are in parentheses. * indicates significance at the 5% level and ** indicates significance at the 1% level. The sample differs slightly from that in Table 1 because individuals with greater than 17000 in total costs for any plan are dropped. All simulated choices are based on the cost distribution generated from the realized costs of 200 individuals in the same decile of 2005 total costs, decile of 2005 total days supply of branded drugs and decile of 2005 days supply of generic drugs. The first three columns compute expected utility using a CRRA utility function with wealth of 17000 and the indicated coefficient of relative risk aversion, assuming that individuals select the choice which maximizes expected utility. The final three columns compute expected utility using a CARA utility function with the indicated coefficient of absolute risk aversion. Variable definitions are otherwise identical to Table 1.

Appendix B: Modeling Private Information

In Part V of the paper we discuss an alternative model that incorporates private information. This appendix presents a formal derivation of that model.

Suppose that utility is given by:

$$u_{ij} = \mu^*_{ij}\beta_1 + \epsilon_{ij} \tag{6}$$

where μ^*_{ij} represents expected costs, defined as the individual's expectations of out of pocket costs at the time when they make their choice (for ease of exposition, we momentarily ignore the premium and variance terms). μ^*_{ij} is not observed. However, we do observe realized costs, which can be written as the sum of expected costs and a noise term, defined as the component of realized costs unknown to the individual at the time of plan choice:

$$C_{ij} = \mu^*_{ij} + \eta_{ij} \tag{7}$$

where C_{ij} denote the realized costs of individual *i* upon enrolling in plan *j*, μ^*_{ij} denotes expected costs, and η_{ij} denotes noise. We can further decompose expected costs into the component of expected costs predictable from 2005 data, μ_{ij}, and the component which is private information, e_{ij}. This yields:

$$C_{ij} = \mu_{ij} + e_{ij} + \eta_{ij} \tag{8}$$

We assume that u_{ij} and e_{ij} are independent of η_{ij}.[24] This assumption implies that individuals are aware at the time when they make their choices of the component of costs that can be predicted based on their previous year's consumption. This "rational

[24] Combined with the additive structure assumed above, the assumption of independence also rules out the case in which the degree of uncertainty about costs varies with the level of expected costs. We relax this strong assumption below by assuming only that μ_{ij} and η_{ij} are conditionally independent given the measured variance of costs.

expectations" assumption is substantive, but conforms with the baseline rational choice model that is implicitly tested by our analysis. We discuss this issue further below.

If this were a linear model, the assumption of independence would be sufficient to identify β_1. This assumption implies that we have a classical measurement error problem: C_{ij} is a noisy measure of μ_{ij}^*. As usual, this problem can be solved with instrumental variables and in this case, μ_{ij} is a valid instrument – it is correlated with μ_{ij}^* and uncorrelated with η_{ij}, so instrumenting for C_{ij} with μ_{ij} would consistently estimate β_1. Because the model is non-linear, we need to be more explicit about the form of the measurement error to obtain consistent estimation. First, we rewrite equation (6) substituting in equation (7):

$$u_{ij} = C_{ij}\beta_1 - \eta_{ij}\beta_1 + \epsilon_{ij} \tag{9}$$

We assume further that $e_{ij} \sim N(0, \tau_{ij}^2)$ and $\eta_{ij} \sim N(0, \sigma_{ij}^2)$. Combined with equation (8) the normal updating formula implies:

$$f(\eta_{ij} | C_{ij}, \mu_{ij}) \sim N\left(\frac{\sigma_{ij}^2}{\sigma_{ij}^2 + \tau_{ij}^2}(C_{ij} - \mu_{ij}), \frac{\tau_{ij}^2 \sigma_{ij}^2}{\sigma_{ij}^2 + \tau_{ij}^2}\right) \tag{10}$$

We do not observe σ_{ij}^2 or τ_{ij}^2. However, provided we assume that $Var(e_{ij} + \eta_{ij} | i, j) = Var(e_{ij} + \eta_{ij} | Z_i, j)$ where Z_i are the variables which define each cell – that is, we assume that there is no heterogeneity in the variance of costs within cells – we do observe $Var(e_{ij} + \eta_{ij}) \equiv \widetilde{\sigma_{ij}^2}$. This is the variance we construct from the 1000 cell exercise. This still leaves us with a separate parameter to identify for each (i,j) pair. We additionally assume that a constant fraction τ_{frac} of the variance of costs within cells is due to private information. That is, we assume that $\tau_{ij}^2 = \tau_{frac}\widetilde{\sigma_{ij}^2}$ and

$\sigma_{ij}^2 = (1 - \tau_{frac})\widetilde{\sigma_{ij}^2}$. As written, this is a random coefficients model with one additional parameter beyond the β's - τ_{frac}, the degree of private information.

How is τ_{frac} identified? Equation (10) suggests a simple intuition. We can think of the model as one with a fixed coefficient β_1 on C_{ij} and a random coefficient with mean $\frac{\beta_1 \sigma_{ij}^2}{\sigma_{ij}^2 + \tau_{ij}^2} = \frac{\beta_1 (1-\tau_{frac})\widetilde{\sigma_{ij}^2}}{\widetilde{\sigma_{ij}^2}} = \beta_1 (1 - \tau_{frac})$ on $C_{ij} - \mu_{ij}$. Thus, the degree of private information is identified by the degree to which the coefficient on $C_{ij} - \mu_{ij}$ falls short of the coefficient on C_{ij}. If individuals have no information beyond what can be predicted from 2005 costs, we will observe $\tau_{frac} = 0$, and equation (9) will simplify to:

$$u_{ij} = C_{ij}\beta_1 - (C_{ij} - \mu_{ij})\beta_1 + \epsilon_{ij} = \mu_{ij}\beta_1 + \epsilon_{ij} \tag{11}$$

If on the other hand individuals have perfect information about 2006 costs, we will observe $\tau_{frac} = 1$, and equation (9) will simplify to:

$$u_{ij} = C_{ij}\beta_1 + \epsilon_{ij} \tag{12}$$

In the interim case, individual's choose based on a linear combination of C_{ij} and μ_{ij}, and the random coefficient on $C_{ij} - \mu_{ij}$ captures the fact that different individuals with the same C_{ij} and μ_{ij} can have varying amounts of private information.

This model also has implications for the variance term and the measurement of risk aversion. The measured variance from the 1000 cell exercise $\widetilde{\sigma_{ij}^2}$ overstates the true variance in costs because some of this variation represents variation in realized costs which is unpredictable based on 2005 costs but is known to the individual at the time when they choose. Thus, the correct variance to use in the model is $(1 - \tau_{frac})\widetilde{\sigma_{ij}^2}$, the variance of the noise term. To the extent that individuals are responsive to the variance term, omitting this correction will tend to bias our estimates of risk aversion downward by a factor of $\frac{1}{1-\tau_{frac}}$.[25]

Reintroducing the variance and the premium term, we obtain:

$$u_{ij} = \pi_{ij}\beta_0 + C_{ij}\beta_1 - \eta_{ij}\beta_1 + (1-\tau_{frac})\widetilde{\sigma_{ij}^2}\beta_2 + \epsilon_{ij} \quad (13)$$

where the distribution of η_{ij} is given by equation (10).

[25] Note that this model does not directly allow for private information about the variance of costs; in some cases, individuals may learn that they are at risk of developing a certain condition which would require treatment with prescription drugs. This knowledge would increase their expected out of pocket costs in the coming year and would also increase the variance in their forecast. The model above does not allow for this type of information; while the model allows individuals in the same cell to have different values of expected costs based on their realization of private information, we continue to assume that all individuals in the same cell in the 1000-cell model face the same variance. To the extent that this assumption is false, our model could be viewed as substituting the predicted variance given the variables used to construct the 1000-cell model for the actual variance.

Appendix C: More General Measurement Error

In the text, we document three choice inconsistencies and argue that they arise as a result of individuals choosing plans with desirable characteristics without regard for whether those characteristics are valuable given their individual circumstances. In this section we consider an alternative hypothesis: could the choice inconsistencies arise as a result of mismeasured out of pocket costs? To investigate this question, we use the simulation model from Appendix A to artificially introduce alternative types of measurement error into our out-of-pocket measure and see how it impacts our results.

We assume that individual's true utility functions are CRRA with coefficient of relative risk aversion equal to 1 (one of the specification's we considered in our original simulation section). We simulate their choices taking the distribution of costs constructed from the 200 individuals in the same cell as the true distribution, and assuming that only this distribution impacts utility. We then estimate our logit models assuming we observe only a noisy measure of out of pocket costs, given by:

$$\widetilde{\mu_{ij}} = \alpha_{ij}\, \mu_{ij}^{*} + x_j\, \delta + e_{ij} \qquad (14)$$

where μ_{ij}^{*} denotes expected out of pocket costs, α_{ij} represent multiplicative errors, e_{ij} represent additive errors and $x_j\, \delta$ represent systematic errors correlated with plan characteristics. In this section, we simulate a number of different specifications for $\widetilde{\mu_{ij}}$. Given each simulation, we compute the variance and cost sharing variables as if $\widetilde{\mu_{ij}}$ is the only variable that we observe. Thus, the noise directly impacts the specification of out of pocket costs, the variance of out of pocket costs, and the average cost sharing term.

Case 1: Idiosyncratic Additive Error

The first case we consider is the case where $\alpha_{ij} = 1$, $\delta = 0$, and $e_{ij} \sim_{iid} N(0, \sigma^2)$ for alternative values of σ^2. The purpose of this case is to show that using predicted costs in place of realized costs effectively instruments for measurement error of this type as it would in a linear model. To choose values for σ^2, we first compute for each individual the standard deviation of out of pocket costs across the plans in their choice set. We then consider σ equal to 5%, 10%, 30% and 50% of this standard deviation.

Appendix Table 2 gives the results for this case. In each model, the coefficient on OOP costs is roughly equal to the coefficient on premiums. For the financial plan characteristics, the third row indicates the dollar value computed by dividing by the coefficient on premiums and multiplying by -100. A few characteristics, such as deductibles, donut hole and quality enter significantly, but in each case the magnitude of the coefficient when converted into dollars by dividing by the coefficient on premiums is 10-100 times smaller than the magnitude estimated in the data (shown in the first column).

Case 2: Idiosyncratic Attrition & Additive Error

In this case, we consider a form of multiplicative error designed to mimic what might be observed if there were attrition due to patients having claims at pharmacies not included in our data. In particular, we assume that $\alpha_{ij} \sim_{iid} U[\mathrm{a}, 1]$ for several alternative values of the lower bound a. We also consider specifications with both attrition and additive error to determine whether the combination of the two might be problematic.

Appendix Table 3 gives the results for this case. The first three specifications (after the original specification) show the impact of increasing the amount of additive noise with a small amount of attrition. The last three show the impact of increasing the degree of attrition for a fixed amount of additive noise (the maximum we consider). A first point to note is that attrition actually biases the coefficient on OOP costs *upward*. If OOP costs were systematically biased downward by 50% for all patients and plans, the coefficient would be biased upwards by 100%. The simulations show that even when the degree of bias varies across plans and individuals, the net result is an upward bias. Plan characteristics enter significantly in some specifications, but the magnitude is substantially smaller than in the model estimated on the real Part D data, and many of the signs are the reverse of what we observe in the data.

Case 3: Systematic by Plan Multiplicative Error

The final simulation we consider is one in which there is a systematic plan-specific error, perhaps because of errors in the crosswalk matching drug IDs in the WK data with drug IDs listed in the formulary. We consider a multiplicative specification to capture the fact that the impact of such errors on OOP costs would likely be proportional to the number of claims an individual possessed. In particular, we assume $\alpha_{ij} \sim_{iid} U[1 - \mathrm{a}, 1 + a]$ (so unlike in the previous section, we allow for the fact that we may overstate OOP costs if we indicate as uncovered drugs which are actually covered).

Appendix Table 4 gives the results for this case. In the specifications with less error, the coefficient is again biased upward. In the specification with $a = 0.5$, the coefficient is biased downward, but it is still about 2/3 as large as the premium coefficient (rather than the 1/3rd we observe in this specification in the actual data). In this last specification, the coefficient on full donut hole coverage is roughly 2/3 what we observe in the data and the coefficient on formularies is actually larger, but the coefficients on the deductible, generic donut hole coverage, cost sharing and quality all have the opposite sign of what we observe in the data.

Appendix Table 2: Idiosyncratic Additive Errors

Additive Error	Original	5%	10%	30%	50%
Premium	-.7843**	-5.444**	-5.435**	-5.277**	-5.049**
(hundreds)	(.0038)	(.0399)	(.0399)	(.0385)	(.0365)
OOP Costs (predicted)	-.2638**	-5.417**	-5.421**	-5.300**	-5.091**
(hundreds)	(.0042)	(.0410)	(.0408)	(.0376)	(.0343)
Variance	.0038**	-.0035**	-.0032**	-.0025**	-.0017**
(times 10^6)	(.0004)	(.0298)	(.0003)	(.0002)	(.0092)
Deductible	-.2304**	-.0515**	-.0478**	-.0158**	.0076
(hundreds)	(.0051)	(.0104)	(.0103)	(.0087)	(.0814)
	-29.38	-0.95	-0.88	-0.30	0.15
Donut Hole	2.890**	-.0882	-.0473	.1989*	.3618**
	(.0186)	(.1059)	(.1046)	(.0902)	(.0814)
	368.48	-1.62	-0.87	3.77	7.17
Generic Coverage	.4102**	-.0639	-.0600	-.0146	-.0350
	(.0141)	(.0799)	(.0797)	(.0788)	(.0779)
	52.30	-1.17	-1.10	-0.28	-0.69
Full Cost Sharing	1.994**	.0043	.0050	.0004	-.0069
	(.0645)	(.0105)	(.0105)	(.0102)	(.0100)
	-0.69	0.00	0.00	0.00	0.00
# of top 100 on Form	.0927**	.0006	.0022	.0073	.0146**
	(.0007)	(.0039)	(.0039)	(.0038)	(.0036)
	11.82	0.01	0.04	0.14	0.29
Avg. Quality	.7406**	-.2126**	-.2153**	-.2327**	-.2657**
	(.0039)	(.0250)	(.0250)	(.0247)	(.0242)
	94.43	-3.91	-3.96	-4.41	-5.26

Notes: Table shows conditional logit results from estimating the model given in equation (6) with measurement error in OOP costs by maximum likelihood. Each column shows coefficients from a single regression. The coefficients reported are the parameters of the utility function, not marginal effects. Standard errors are in parentheses, followed by the dollar value of the coefficients computed by normalizing by the coefficient on premiums. * indicates significance at the 5% level and ** indicates significance at the 1% level. The sample differs slightly from that in Table 1 because individuals with greater than 17000 in total costs for any plan are dropped. All simulated choices are based on the cost distribution generated from the realized costs of 200 individuals in the same decile of 2005 total costs, decile of 2005 total days supply of branded drugs and decile of 2005 days supply of generic drugs. The first column shows the coefficients from the model estimated on the actual data (the coefficients differ slightly from those in Table 1 because predicted costs is used in lieu of realized costs). Columns (2)-(5) introduce normally distributed measurement error which is i.i.d. across plans and individuals with standard deviation equal to the indicated percentage of the standard deviation of OOP cost computed for each individual based on their choice set. Variable definitions are otherwise identical to Table 1.

Appendix Table 3: Idiosyncratic Attrition & Additive Error

a		.9	.9	.9	.75	0.5
Additive Error	Original	5%	30%	50%	50%	50%
Premium	-.7843**	-5.412**	-5.237**	-4.906**	-4.732**	4.121**
(hundreds)	(.0038)	(.0397)	(.0381)	(.0353)	(.0339)	(.0286)
OOP Costs (predicted)	-.2638**	-5.692**	-5.576**	-5.177**	-5.423**	5.483**
(hundreds)	(.0042)	(.0431)	(.0393)	(.0346)	(.0356)	(.0345)
Variance	.0038**	-.0033**	-.0016**	-.0017**	-.0025**	.0020**
(times 10^6)	(.0004)	(.0003)	(.0002)	(.0001)	(.0076)	(.0069)
Deductible	-.2304**	-.0418**	.0033	.0271**	.0288**	.0889**
(hundreds)	(.0051)	(.0101)	(.0086)	(.0075)	(.0070)	(.0058)
	-29.38	-0.77	0.06	0.55	0.61	2.16
Donut Hole	2.890**	.0577	.3800**	.5095**	.4495**	.7577**
	(.0186)	(.1040)	(.0891)	(.0780)	(.0760)	(.0679)
	368.48	1.07	7.26	10.39	9.50	18.39
Generic Coverage	.4102**	-.0366	.0350	.0311	-.0220	-.0453
	(.0141)	(.0798)	(.0786)	(.0765)	(.0763)	(.0733)
	52.30	-0.68	0.67	0.63	-0.46	-1.10
Full Cost Sharing	1.994**	.0104	.0133	.0031	-.0050	.0408*
	(.0645)	(.0117)	(.0119)	(.0119)	(.0135)	(.0191)
	-0.69	0.19	0.25	0.06	-0.11	0.99
# of top 100 on Form	.0927**	.0026	.0120**	.0167**	.0161**	.0307**
	(.0007)	(.0039)	(.0038)	(.0036)	(.0036)	(.0034)
	11.82	0.05	0.23	0.34	0.34	0.74
Avg. Quality	.7406**	-.2231**	-.2293**	-.2687**	-.3185**	.4196**
	(.0039)	(.0251)	(.0247)	(.0238)	(.0236)	(.0024)
	94.43	-4.12	-4.38	-5.48	-6.73	-10.18

Notes: Table shows conditional logit results from estimating the model given in equation (6) with measurement error in OOP costs by maximum likelihood. Each column shows coefficients from a single regression. The coefficients reported are the parameters of the utility function, not marginal effects. Standard errors are in parentheses, followed by the dollar value of the coefficients computed by normalizing by the coefficient on premiums. * indicates significance at the 5% level and ** indicates significance at the 1% level. The sample differs slightly from that in Table 1 because individuals with greater than 17000 in total costs for any plan are dropped. All simulated choices are based on the cost distribution generated from the realized costs of 200 individuals in the same decile of 2005 total costs, decile of 2005 total days supply of branded drugs and decile of 2005 days supply of generic drugs. The first column shows the coefficients from the model estimated on the actual data (the coefficients differ slightly from those in Table 1 because predicted costs is used in lieu of realized costs). Columns (2)-(5) introduce a combination of additive error as in Appendix Table 2, and multiplicative attrition on OOP costs i.i.d. across plans and individuals drawn as a $U[a, 1]$ random variable. Variable definitions are otherwise identical to Table 1.

Appendix Table 4: Systematic Plan-Specific Error

a	Original	.05	0.1	0.3	0.5
Premium	-.7843**	-4.221**	-3.203**	-1.564**	-1.412**
(hundreds)	(.0038)	(.0295)	(.0195)	(.0087)	(.0078)
OOP Costs (predicted)	-.2638**	-4.488**	-3.621**	-1.957**	-.9768**
(hundreds)	(.0042)	(.0327)	(.0246)	(.0114)	(.0086)
Variance	.0038**	.0022**	.0077**	.0126**	.0083**
(times 10^6)	(.0004)	(.0003)	(.0002)	(.0001)	(.0001)
Deductible	-.2304**	-.0096	.1823**	.5777**	.4927**
(hundreds)	(.0051)	(.0096)	(.0081)	(.0055)	(.0054)
	-29.38	-0.23	5.69	36.94	34.89
Donut Hole	2.890**	1.496**	3.404**	3.983**	3.741**
	(.0186)	(.0832)	(.0587)	(.0332)	(.0299)
	368.48	35.44	106.28	254.67	264.94
Generic Coverage	.4102**	.5150**	.3169**	-.1309*	-.1525**
	(.0141)	(.0737)	(.0681)	(.0619)	(.0612)
	52.30	12.20	9.89	-8.37	-10.80
Full Cost Sharing	1.994**	-.2803**	-.2852**	-.3423**	-.2203**
	(.0645)	(.0096)	(.0088)	(.0074)	(.0078)
	254.24	-6.64	-8.90	-21.89	-15.60
# of top 100 on Form	.0927**	.0264**	.1026**	.2569**	.2804**
	(.0007)	(.0037)	(.0038)	(.0034)	(.0034)
	11.82	0.63	3.20	16.43	19.86
Avg. Quality	.7406**	-.4968**	-.7256**	-1.056**	-1.047**
	(.0039)	(.0242)	(.0210)	(.0150)	(.0137)
	94.43	-11.77	-22.65	-67.52	-74.15

Notes: Table shows conditional logit results from estimating the model given in equation (6) with measurement error in OOP costs by maximum likelihood. Each column shows coefficients from a single regression. The coefficients reported are the parameters of the utility function, not marginal effects. Standard errors are in parentheses, followed by the dollar value of the coefficients computed by normalizing by the coefficient on premiums. * indicates significance at the 5% level and ** indicates significance at the 1% level. The sample differs slightly from that in Table 1 because individuals with greater than 17000 in total costs for any plan are dropped. All simulated choices are based on the cost distribution generated from the realized costs of 200 individuals in the same decile of 2005 total costs, decile of 2005 total days supply of branded drugs and decile of 2005 days supply of generic drugs. The first column shows the coefficients from the model estimated on the actual data (the coefficients differ slightly from those in Table 1 because predicted costs is used in lieu of realized costs). Columns (2)-(5) introduce multiplicative error given by i.i.d. random draws for each plan from a $U[1-a, 1+a]$ random variable. Variable definitions are otherwise identical to Table 1.