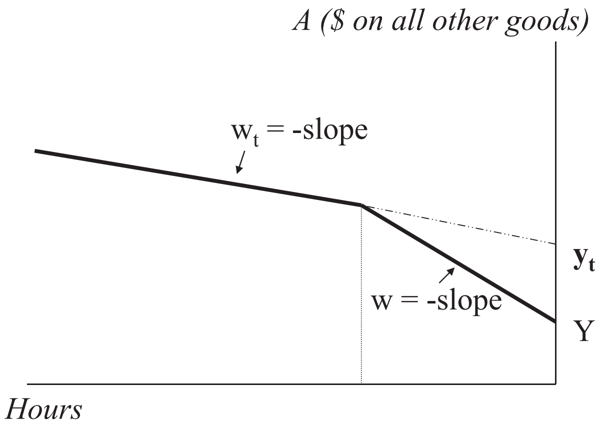
A Online Appendix
Comparison to Nonlinear Budget Set Literature

My paper builds on the nonlinear budget set literature that estimated the labor supply elasticity using nonlinear budget sets induced by progressive taxes. Hausman (1985) provides a survey of the early literature.[1] To facilitate comparison of the nonlinear budget set in my application to

Figure A1: Reference Case: Nonlinear Budget Set Under Simple Progressive Tax



the nonlinear budget set in the labor supply application, Figure A1 depicts a nonlinear budget set induced by a simple progressive tax. The after-tax wage, w, that a worker faces varies with the tax rate, t.[2] The labor supply application examines the effect of the after-tax wage (the slope) on hours (the horizontal axis) controlling for income (the vertical axis). Similarly, I examine the effect the marginal price (the slope) on quantity of medical care consumed in dollars (the horizontal axis) controlling for income (the vertical axis). As is apparent from the comparison of Figure 1 to Figure A1, the budget set induced by health insurance is inherently nonconvex, but the budget set induced by progressive taxes is generally convex.

Some difficulties that are present in the labor supply application are not present in my application. For example, in the labor supply application, one important issue is that several individuals work zero hours, and the potential wage for these individuals is unknown. The medical care application does not suffer from this difficulty, however. Although several individuals do not consume any medical care, the price that they would face is observable because it is determined by the insurance policy. This transparency is possible because, unlike the wage, the price does not vary at the individual level.

[1] Some early estimates of the labor supply elasticity using nonlinear budget set models include Hurd (1976), Rosen (1979), and Burtless and Moffit (1985). Other applications of the nonlinear budget set model include the demand for air conditioners in Hausman (1979), the disability insurance program in Halpern and Hausman (1986), the Social Security earnings test in Friedberg (2000), and 401(k) saving in Engelhardt and Kumar (2007). However, the labor supply elasticity remains the most prevalent application of the nonlinear budget set model.

[2] Comparison with Figure 1 is slightly difficult because hours are a "bad," but both figures are drawn so that the hypothetical arrow of increasing preference points to the upper right.

One advantage of the transparency of the price schedule in the budget set for medical care is that the agent and the econometrician are likely to be aware of the agent's current segment on the budget set. Liebman and Zeckhauser (2004) hypothesize that individuals respond suboptimally to complex schedules - a phenomena they call "schmeduling." While "schmeduling" may be very likely with respect to the complex tax rules addressed by the labor supply elasticity estimates, it is arguably less likely with respect to health insurance because the price schedule is so simple. In the labor supply application, since the slope of each segment varies with the underlying marginal wage, the exact segment is often unknown to the econometrician and possibly to the agent.

The transparency of the price schedule in the medical care application comes at the cost of reduced underlying variation for identification. Blomquist and Newey (2002) have developed nonparametric techniques to estimate nonlinear budget set models which have been applied by Kumar (2004) and others. These nonparametric techniques would likely have less power in this application because the slopes of the segments of the budget set do not vary across individuals. More importantly, the Blomquist and Newey (2002) approach requires that the budget set be convex.

The main contribution that I make to the class of nonlinear budget set models is that I can use my model to estimate the tradeoff between moral hazard and risk protection for a given individual, within a nonlinear health insurance plan. In the labor supply context, my model could be applied to study the tradeoff between labor supply disincentives and risk protection associated with the nonlinear subsidy structure of disability insurance or the earned income tax credit. This problem differs from the tradeoff between moral hazard and risk protection considered by Baily (1978) and generalized by Chetty (2006), because risk protection in those studies is measured by *consumption smoothing* over time instead of the generosity of a particular benefit schedule before the risk is realized.

I am aware of at least three other studies that have incorporated risk aversion into models of labor supply, but their models do not allow for measurement of the analog to the tradeoff that I consider in the medical care context. Halpern and Hausman (1986) model the decision to apply for the social security disability insurance program in the face of uncertainty about acceptance, and risk aversion informs the decision of whether or not to apply, but the authors do not consider the tradeoff between moral hazard and risk protection that the benefit schedule induces for those who are accepted. Relatedly, recent work by Low and Pistaferri (2010) considers the tradeoff between the cost of giving disability insurance to individuals who are not disabled and discouraging those who are disabled from applying, but it abstracts away from the tradeoff between moral hazard and risk protection for enrollees. Finally, Chetty (2006b) demonstrates that there is a fundamental relationship between labor supply elasticities and risk aversion, and he uses elasticity estimates from other studies to estimate risk aversion. In the health insurance context, I demonstrate a related fundamental relationship between price elasticities (moral hazard) and risk aversion, which could in turn have implications for the labor literature. In addition to developing the theoretical framework, I estimate my model using administrative data.

B Discussion of Conditions for Integrability

Symmetry and negativity of the Slutsky matrix is necessary to recover preferences from demand. (See Mas-Collell et al. (1995)) In a partial equilibrium model, the Slutsky matrix is necessarily symmetric. From the Slutsky equation, the Slutsky matrix S is defined as

$$S = \frac{\partial Q(y_s, p_s)}{\partial p_s} + \frac{\partial Q(y_s, p_s)}{\partial y_s} Q(y_s, p_s).$$

In the nonlinear budget set literature, Slutsky conditions have received a great deal of attention. In the labor supply literature, the Slutsky condition can be satisfied globally if the labor supply elasticity is positive and the income elasticity is negative, but it is not automatically satisfied. MaCurdy et al. (1990) and MaCurdy (1992) brought attention to the role of Slutsky condition in the labor supply literature and proposed an alternative local linearization method to smooth around the kinks in the budget set and relax the Slutsky condition. However, Blomquist (1995) shows that even under local linearization, the Slutsky condition must be satisfied for the estimated parameters to be interpreted as labor supply parameters. He also shows that neither method automatically produces parameter estimates that satisfy the Slutsky condition. More recently, Heim and Meyer (2003) emphasize that though the MaCurdy work is valuable because it demonstrates where the Slutsky condition matters, it does not provide an alternative method.

C Variation in the Tradeoff Across Demographic Groups

While Table 4 focuses on average spending, Table C1 shows how predicted spending varies with covariates. The first panel shows actual spending, and the second panel shows predicted spending by plan for different demographic groups. Groups with higher actual spending, such as women, individuals over median age, and hourly employees, also have higher predicted spending. We do not see a clear monotonic pattern in actual spending by income quartile, and we also do not see a clear pattern in predicted spending by income quartile. Among all demographic groups shown, insurer spending is higher under the Feldstein plan than it is under the \$1,000 deductible plan. The descriptive comparison of generosity across plans and by covariates does not allow us to make statements about consumer welfare across plans because consumers must pay for extra plan generosity, and this simple exercise does not tell us how much they value extra plan generosity.

Tables C2 and C3 provide more insight into the nature of heterogeneity in the welfare impact of insurance by presenting welfare analysis by covariates. These tables show that observed heterogeneity goes a long way in explaining the variation across the valuation quantiles. Table C2 shows the welfare gain from insurance in the first and second period for distinct demographic groups. We see that the welfare gains that we estimate from insurance in Table C2 are very similar to predicted insurer spending reported in Table C1; demographic groups with higher predicted insurer spending derive a larger welfare gain from insurance than demographic groups with lower predicted insurer spending. As we see in Table C3, demographic groups with larger predicted insurer spending also have larger deadweight losses. For example, women have predicted insurer spending that is almost

Table C1: Counterfactual Simulation Results: Spending By Covariates

		Mean By Sex		Mean By Income Quartile				Mean By Age		Mean By Type	
				(Low)			(High)	Age<	Age>		
	Mean	Male	Female	1	2	3	4	med	med	Salary	Hourly
Actual Spending											
Offered											
All plans	2,335	1,675	2,728	2,272	2,417	2,303	2,353	1,510	3,205	1,818	2,378
$350 Deductible	2,637	1,981	2,968	2,584	2,721	2,630	2,614	1,710	3,516	2,103	2,678
$500 Deductible	1,779	1,315	2,148	1,701	1,920	1,610	1,908	1,236	2,431	1,302	1,833
$750 Deductible	1,412	943	1,818	1,285	1,451	1,317	1,626	1,142	1,847	1,065	1,446
$1,000 Deductible	1,147	868	1,465	1,128	1,186	1,104	1,180	795	1,737	1,128	1,149
Predicted Spending, Censored at 27,500											
Offered											
$350 Deductible	1,956	1,330	2,329	1,951	1,964	1,945	1,966	1,335	2,611	1,528	1,992
$500 Deductible	1,956	1,330	2,329	1,951	1,963	1,945	1,966	1,334	2,611	1,528	1,992
$750 Deductible	1,956	1,329	2,329	1,950	1,963	1,945	1,966	1,334	2,611	1,527	1,992
$1,000 Deductible	1,955	1,329	2,329	1,949	1,963	1,945	1,966	1,333	2,611	1,527	1,991
Hypothetical											
50% Frac to $2,000 Deduct	1,955	1,328	2,328	1,948	1,962	1,944	1,966	1,333	2,610	1,526	1,991
0% Frac (Full Insurance)	1,959	1,332	2,332	1,957	1,966	1,947	1,967	1,336	2,615	1,530	1,995
20% Frac	1,956	1,330	2,329	1,951	1,963	1,945	1,966	1,335	2,611	1,528	1,992
40% Frac	1,953	1,328	2,326	1,945	1,961	1,944	1,966	1,333	2,607	1,526	1,989
50% Frac	1,952	1,327	2,324	1,942	1,959	1,943	1,966	1,332	2,605	1,524	1,988
60% Frac	1,950	1,326	2,322	1,938	1,957	1,942	1,966	1,331	2,603	1,523	1,986
80% Frac	1,947	1,324	2,318	1,930	1,954	1,940	1,965	1,329	2,598	1,521	1,983
100% Frac (No Insurance)	1,943	1,322	2,314	1,922	1,950	1,938	1,965	1,327	2,593	1,518	1,979
Predicted Insurer Spending, INS_{ij}											
Offered											
$350 Deductible	1,292	796	1,587	1,288	1,298	1,283	1,299	795	1,815	950	1,321
$500 Deductible	1,174	688	1,464	1,170	1,180	1,166	1,181	685	1,689	838	1,202
$750 Deductible	991	533	1,264	987	998	984	998	519	1,489	669	1,018
$1,000 Deductible	822	406	1,070	818	828	815	828	378	1,290	520	847
Hypothetical											
50% Frac to $2,000 Deduct	1,106	719	1,336	1,101	1,111	1,100	1,113	707	1,527	829	1,129
0% Frac (Full Insurance)	1,959	1,332	2,332	1,957	1,966	1,947	1,967	1,336	2,615	1,530	1,995
20% Frac	1,565	1,064	1,863	1,561	1,571	1,556	1,573	1,068	2,089	1,222	1,594
40% Frac	1,172	797	1,396	1,167	1,176	1,166	1,180	800	1,564	915	1,194
50% Frac	976	664	1,162	971	980	971	983	666	1,303	762	994
60% Frac	780	531	929	775	783	777	786	532	1,041	609	794
80% Frac	389	265	464	386	391	388	393	266	520	304	397
100% Frac (No Insurance)	0	0	0	0	0	0	0	0	0	0	0

Values in dollars.
Median age is 43. Income first quartile: $30,208; median: $37,222; third quartile: $49,113.
Median actual spending: $242; 75th percentile: $1,420; 99th percentile: $32,193.

twice as large as that for men. The welfare gain from insurance in each period and the deadweight loss from moral hazard is also roughly twice as large for women as it is for men. Risk protection does not appear to vary with predicted insurer spending because the magnitudes of the risk protection premium are so small, but there is also some variation in the risk protection premium across demographic groups.

Table C2: Counterfactual Simulation Results: Welfare in First and Second Period by Covariates

		Mean By Sex		Mean By Income Quartile				Mean By Age		Mean By Type	
				(Low)			(High)	Age<	Age>		
	Mean	Male	Female	1	2	3	4	med	med	Salary	Hourly
Welfare Gain From Insurance in First Period Before Premium, π_{ij}											
Offered											
$350 Deductible	1,286	792	1,581	1,276	1,292	1,281	1,298	792	1,807	946	1,315
$500 Deductible	1,169	685	1,457	1,158	1,175	1,163	1,181	682	1,682	834	1,197
$750 Deductible	986	530	1,258	975	992	981	997	516	1,482	665	1,013
$1,000 Deductible	817	403	1,064	806	823	813	827	375	1,283	517	842
Hypothetical											
50% Frac to $2,000 Deduct	1,102	717	1,331	1,091	1,107	1,097	1,112	705	1,520	826	1,125
0% Frac (Full Insurance)	1,951	1,327	2,323	1,940	1,958	1,942	1,966	1,331	2,604	1,524	1,987
20% Frac	1,560	1,061	1,857	1,549	1,565	1,553	1,572	1,064	2,081	1,218	1,588
40% Frac	1,169	795	1,392	1,160	1,173	1,164	1,179	798	1,560	913	1,190
50% Frac	974	662	1,159	965	977	970	983	665	1,299	761	991
60% Frac	779	529	927	772	781	776	786	531	1,039	608	793
80% Frac	389	265	463	385	390	388	393	266	519	304	396
100% Frac (No Insurance)	0	0	0	0	0	0	0	0	0	0	0
Welfare Gain From Insurance in Second Period Before Premium, ω_{ij}											
Offered											
$350 Deductible	1,286	792	1,581	1,276	1,292	1,280	1,298	792	1,807	946	1,315
$500 Deductible	1,169	685	1,457	1,158	1,175	1,163	1,180	682	1,682	834	1,197
$750 Deductible	986	530	1,258	975	992	981	997	516	1,482	665	1,013
$1,000 Deductible	817	403	1,064	806	823	813	827	375	1,283	517	842
Hypothetical											
50% Frac to $2,000 Deduct	1,102	717	1,331	1,091	1,107	1,097	1,112	705	1,520	826	1,125
0% Frac (Full Insurance)	1,951	1,327	2,323	1,940	1,958	1,942	1,966	1,331	2,604	1,524	1,987
20% Frac	1,560	1,061	1,857	1,549	1,565	1,553	1,572	1,064	2,081	1,218	1,588
40% Frac	1,169	795	1,392	1,160	1,173	1,164	1,179	798	1,560	913	1,190
50% Frac	974	662	1,159	965	977	970	983	665	1,299	760	991
60% Frac	779	529	927	772	781	776	786	531	1,039	608	793
80% Frac	389	265	463	385	390	388	393	266	519	304	396
100% Frac (No Insurance)	0	0	0	0	0	0	0	0	0	0	0

Values in dollars.
Median age is 43. Income first quartile: $30,208; median: $37,222; third quartile: $49,113.
Median actual spending: $242; 75th percentile: $1,420; 99th percentile: $32,193.

D Implications for Optimal Insurance

Counterfactual simulations from my model allow me to consider the optimal nonlinear structure of health insurance plans, given the tradeoff between moral hazard and risk protection. If there is no moral hazard and agents are risk averse, then there will be a net welfare gain from any insurance, with the highest gain for full insurance, so full insurance will be optimal. Conversely, when there is moral hazard and agents are not risk averse, there will be a net welfare loss from any insurance, with the largest loss for full insurance, so no insurance will be optimal. In the presence of nonzero risk aversion and nonzero moral hazard, it might seem to follow that partial insurance will be optimal, but partial insurance need not be optimal.

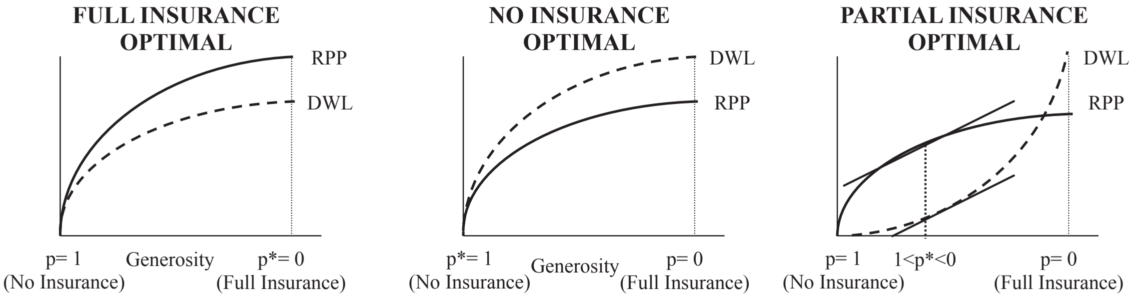
In Figure D1, I depict optimal insurance under three scenarios. All three scenarios assume that generosity can be represented as a single index. For example, consider a succession of linear plans in which the price to the consumer decreases from one to zero. In the left scenario, as generosity

Table C3: Counterfactual Simulation Results: DWL and RPP By Covariates

		Mean By Sex		Mean By Income Quartile				Mean By Age		Mean By Type	
				(Low)			(High)	Age<	Age>		
	Mean	**Male**	**Female**	**1**	**2**	**3**	**4**	**med**	**med**	**Salary**	**Hourly**
RPP $_{ij}$											
Offered											
$350 Deductible	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
$500 Deductible	0.04	0.03	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
$750 Deductible	0.04	0.03	0.04	0.04	0.04	0.04	0.04	0.03	0.04	0.03	0.04
$1,000 Deductible	0.03	0.02	0.04	0.03	0.03	0.03	0.03	0.03	0.04	0.03	0.03
Hypothetical											
50% Frac to $2,000 Deduct	0.03	0.03	0.04	0.03	0.03	0.04	0.04	0.03	0.04	0.03	0.04
0% Frac (Full Insurance)	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
20% Frac	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
40% Frac	0.04	0.03	0.04	0.03	0.04	0.04	0.04	0.04	0.04	0.03	0.04
50% Frac	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
60% Frac	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
80% Frac	0.02	0.01	0.02	0.01	0.02	0.02	0.02	0.02	0.02	0.01	0.02
100% Frac (No Insurance)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
DWL $_{ij}$											
Offered											
$350 Deductible	5.52	3.58	6.68	12.43	5.70	2.96	0.80	3.32	7.84	4.08	5.64
$500 Deductible	5.36	3.42	6.52	12.07	5.54	2.88	0.78	3.23	7.61	3.96	5.48
$750 Deductible	5.23	3.21	6.44	11.78	5.41	2.81	0.76	3.07	7.52	3.80	5.36
$1,000 Deductible	5.04	2.90	6.32	11.34	5.22	2.70	0.74	2.75	7.45	3.53	5.17
Hypothetical											
50% Frac to $2,000 Deduct	4.35	2.40	5.51	9.77	4.51	2.34	0.63	2.03	6.80	2.81	4.48
0% Frac (Full Insurance)	7.82	5.16	9.41	17.64	8.05	4.18	1.14	4.93	10.87	5.95	7.98
20% Frac	5.44	3.55	6.57	12.26	5.62	2.92	0.79	3.35	7.65	4.08	5.56
40% Frac	3.33	2.15	4.03	7.47	3.44	1.79	0.49	2.00	4.73	2.46	3.40
50% Frac	2.41	1.55	2.92	5.40	2.49	1.30	0.35	1.43	3.44	1.76	2.46
60% Frac	1.60	1.03	1.95	3.59	1.66	0.87	0.23	0.94	2.30	1.17	1.64
80% Frac	0.43	0.28	0.53	0.97	0.45	0.23	0.06	0.25	0.63	0.31	0.44
100% Frac (No Insurance)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(RPP-DWL) $_{ij}$											
Offered											
$350 Deductible	-5.48	-3.55	-6.63	-12.39	-5.66	-2.92	-0.76	-3.29	-7.80	-4.04	-5.60
$500 Deductible	-5.32	-3.38	-6.48	-12.03	-5.50	-2.84	-0.74	-3.19	-7.57	-3.93	-5.44
$750 Deductible	-5.20	-3.18	-6.40	-11.75	-5.37	-2.77	-0.73	-3.03	-7.48	-3.77	-5.32
$1,000 Deductible	-5.01	-2.87	-6.28	-11.31	-5.18	-2.67	-0.70	-2.73	-7.41	-3.51	-5.13
Hypothetical											
50% Frac to $2,000 Deduct	-4.32	-2.37	-5.48	-9.74	-4.48	-2.31	-0.60	-2.00	-6.76	-2.77	-4.45
0% Frac (Full Insurance)	-7.78	-5.12	-9.36	-17.60	-8.01	-4.14	-1.09	-4.89	-10.82	-5.91	-7.94
20% Frac	-5.40	-3.51	-6.53	-12.22	-5.58	-2.88	-0.75	-3.31	-7.61	-4.04	-5.52
40% Frac	-3.29	-2.11	-3.99	-7.44	-3.41	-1.75	-0.45	-1.96	-4.69	-2.42	-3.36
50% Frac	-2.37	-1.52	-2.89	-5.37	-2.46	-1.26	-0.32	-1.40	-3.41	-1.73	-2.43
60% Frac	-1.58	-1.00	-1.92	-3.57	-1.64	-0.84	-0.21	-0.91	-2.27	-1.14	-1.61
80% Frac	-0.42	-0.26	-0.51	-0.95	-0.44	-0.22	-0.05	-0.23	-0.61	-0.30	-0.43
100% Frac (No Insurance)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Values in dollars.
Median age is 43. Income first quartile: $30,208; median: $37,222; third quartile: $49,113.
Median actual spending: $242; 75th percentile: $1,420; 99th percentile: $32,193.

Figure D1: Optimal Insurance



increases, RPP always grows at a faster rate than DWL, implying that full insurance is optimal (marginal RPP exceeds marginal DWL for every level of generosity, so we have a corner solution at full insurance). In the middle scenario, as generosity increases, DWL always grows at a faster rate than RPP, implying that zero insurance is optimal. In the third scenario, DWL and RPP grow at different rates as generosity increases, and the optimum occurs where marginal DWL is equal to marginal RPP. Partial insurance is only optimal in the case where risk protection increases at a decreasing rate and moral hazard increases at a decreasing rate as generosity increases.

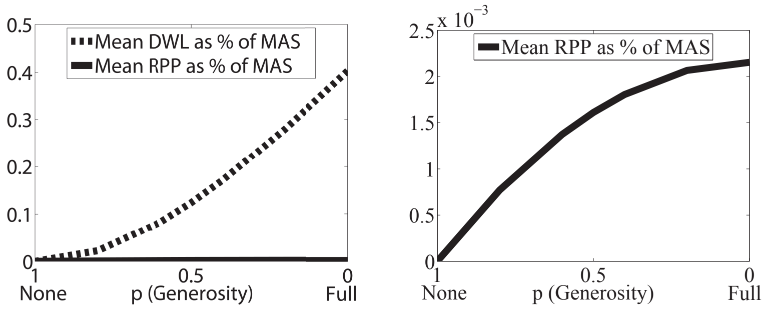
The key in recognizing that partial insurance need not be optimal is that deadweight loss and risk protection always move in the same direction, as drawn in Figure D1. To see why, conduct a thought experiment: think of a linear or nonlinear plan that will decrease moral hazard but will increase risk protection for the same individual. It is not possible to construct such a plan for a single individual. This example gives a concrete example of why it is beneficial to consider moral hazard and risk protection jointly: in my model, they must always move in the same direction.[3]

In Figure D2, I construct the empirical analog of Figure D1 using the results from my counterfactual simulations, which vary the marginal price in plans with linear cost sharing from 1 to 2. These results are reported in Table 6. In the left subfigure, it is difficult to see RPP because it coincides with the horizontal axis, but the right subfigure graphs RPP separately on a different scale. The figure shows that in my empirical context, DWL grows at increasing rate, while risk protection grows at a decreasing rate, suggesting that partial insurance will be optimal. However, the level of deadweight loss is so much larger than the level of risk protection that the optimal level of partial insurance will be very close to zero.

This result stands in contrast to the result reported by Manning and Marquis (1996) from a similar exercise. They also find that as generosity increases, DWL increases at an increasing rate, and RPP increases at a decreasing rate, implying that partial insurance is optimal. But they find that much more generous insurance, insurance with a 45% coinsurance rate, is optimal. There

[3]This observation does not seem to have been obvious in the literature. For example, in Feldstein and Gruber (1995), the authors consider a counterfactual exercise in which they move agents into new plans. Although they always estimate a reduction in DWL, they sometimes find reductions and sometimes find increases in risk protection. Such a finding is not possible in my model, which considers both sides of the tradeoff simultaneously.

Figure D2: Estimates of Optimal Insurance with Varying Linear Price



(a) DWL and RPP (b) RPP Only (Different Scale)

could be several reasons for why my result differs from theirs, including differences in modeling assumptions and differences in the underlying data.[4]

I caution against taking the implications of my results for optimal insurance too literally because, as discussed above, I do not observe any agents with full insurance or zero insurance in my data. However, the counterfactual simulations demonstrate how such an analysis could be undertaken using counterfactual simulations derived from an empirical context with a wider range of observed insurance generosities. Another reason not to take the results literally is that restricting insurance contracts to be linear likely imposes severe restrictions on welfare gains, which is why empirically, many plans have stoplosses. The consideration of optimal insurance structures should allow for the nonlinear cost sharing schedules used in practice. My model allows for counterfactual simulations using complex nonlinear plans.

Although the simple simulations in Figure D2 show smaller welfare in more generous plans, when generosity is measured in only one dimension at a time (the coinsurance rate), this result does not hold more generally. If we increase generosity in one dimension and decrease it in another, even if we can calculate the net impact on how much the insurer will pay, we need the model to calculate the net impact on welfare. Returning to the comparison of the $1,000 deductible plan to the Feldstein plan, the Feldstein plan results in higher insurer spending for individuals with total spending below $1,000 because the insurer now pays 50% of spending before the deductible as opposed to 0%. However, for individuals with over $1,000 of spending, the Feldstein plan results in lower insurer spending because the insurer now pays 50% of spending as opposed to 80%. Whether the Feldstein plan is more or less generous on net depends on the empirical distribution of agents. As shown in Table 4, the counterfactual simulation without the model suggests that the Feldstein plan is less generous than the $1,000 deductible plan, and the counterfactual simulation with the model suggests that the Feldstein plan is more generous than the $1,000 deductible plan. Despite the increase in modeled generosity from the $1,000 deductible plan to the Feldstein plan, the welfare calculations in Table 6 show an increase in average welfare from the $1,000 deductible plan to the Feldstein plan. This exercise demonstrates the need for a model that considers all segments of the

[4]Manning and Marquis (1996) are limited to simple simulations in which plans only have two segments. The ability of my model to handle an unlimited number of segments allows me to apply it to more recent data and to conduct richer counterfactual plans such as the Feldstein plan.

health insurance plans.

Knowledge of how DWL and RPP change as plan structure changes is relevant for insurance design. Though the empirical results from the simple simulation presented here suggests that very limited *linear* insurance is optimal, allowing for nonlinearities could improve the optimality of insurance. Furthermore, society might weight other factors against the net welfare gain from moral hazard and risk protection. For example, agents and society might decide to insure for other reasons such as externalities, paternalism, or behavioral factors. If these other factors are present, optimal insurance trades off the welfare implications of addressing these factors against the net welfare gain from moral hazard and risk protection calculated here.