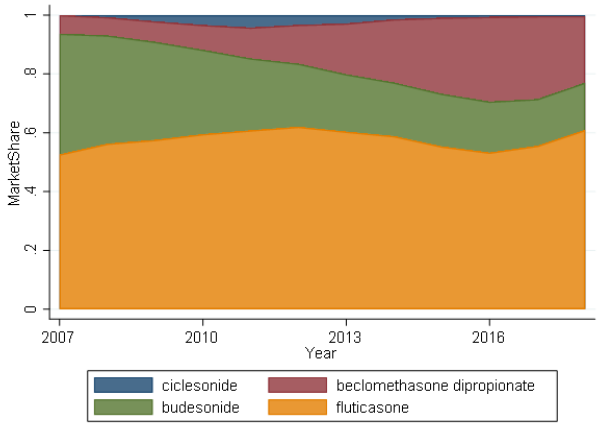
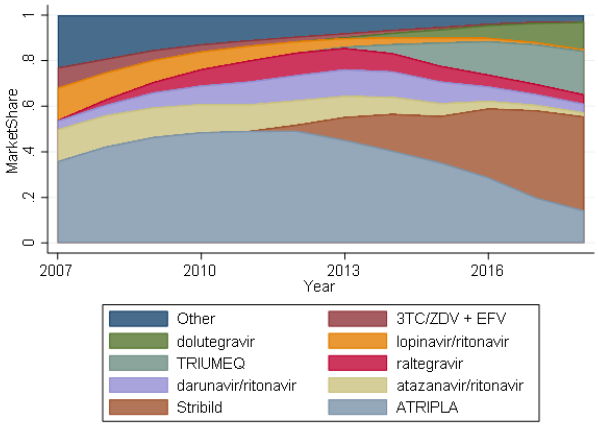
Online Appendix OA.A Results for Other Conditions

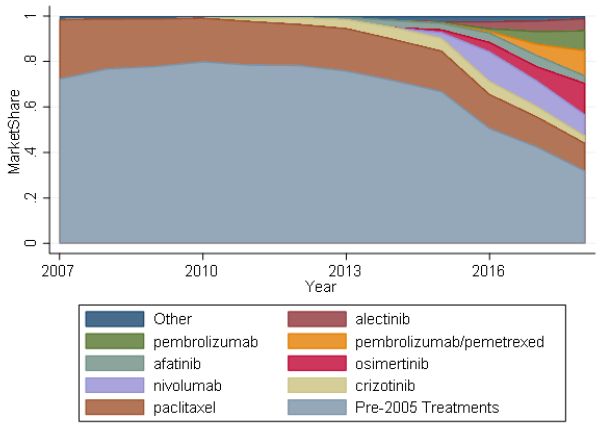
Figure OA1: Market Share for the Top Treatments Over Time For Conditions Not Shown in the Main Text



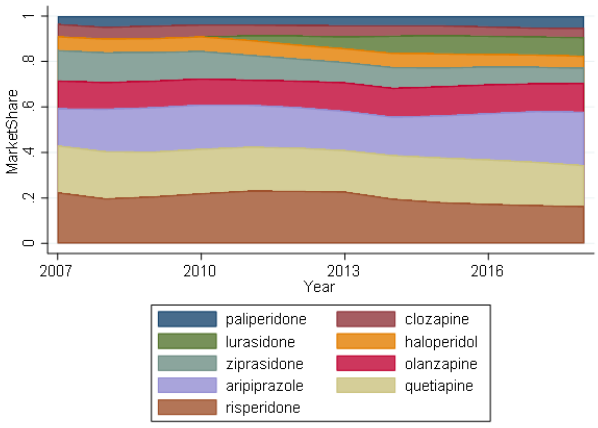
(a) Asthma



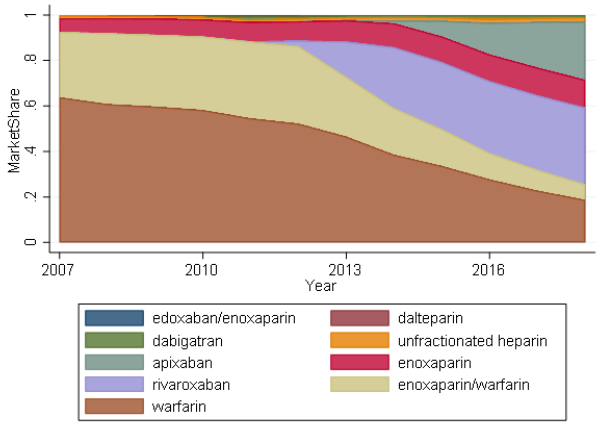
(b) HIV



(c) Lung Cancer



(d) Schizophrenia



(e) Venous Thromboembolism

Notes: These figures present the market shares by year for up to the 9 highest volume drugs for conditions not shown in the main text. These graphs use MarketScan data.

Figure OA2: QALY Estimates for Individual Treatments for Conditions Not Shown in the Main Text

(a) Asthma

	(1) Is Baseline Treatment	(2) Δ QALYs from Baseline
beclomethasone_dipropionate	0	0.005
budesonide	0	-0.007
ciclesonide	0	-0.089
fluticasone	1	0.000

(b) Atrial Fibrillation

	(1) Is Baseline Treatment	(2) Δ QALYs from Baseline
apixaban	0	0.358
clopidogrel	0	-2.540
dabigatran	0	0.269
edoxaban	0	0.327
rivaroxaban	0	0.164
warfarin	1	0.000

(c) Colon Cancer

	(1) Is Baseline Treatment	(2) Δ QALYs from Baseline
bevacizumab/5-FU/irinotecan	0	0.573
bevacizumab/5-FU/oxaliplatin	0	0.399
bevacizumab/capecitabine	0	1.270
capecitabine	0	0.165
capecitabine/oxaliplatin	0	0.105
cetuximab/irinotecan	0	0.904
fluorouracil/leucovorin	0	-0.073
fluorouracil/oxaliplatin	0	0.155
fluorouracil_(5-FU)	1	0.000

(d) Cystic Fibrosis

	(1) Is Baseline Treatment	(2) Δ QALYs from Baseline
Orkambi	0	0.888
aztreonam/dornase_alfa	0	0.208
colistimethate/dornase_alfa	0	-0.183
dornase_alfa	0	-0.002
dornase_alfa/tobramycin	1	0.000

(e) HIV

	(1) Is Baseline Treatment	(2) Δ QALYs from Baseline
3TC/ZDV_+_EFV	0	-0.322
ATRIPLA	1	0.000
Stribild	0	0.045
TRIUMEQ	0	0.188
atazanavir/ritonavir	0	0.086
darunavir/ritonavir	0	0.274
dolutegravir	0	0.343
lopinavir/ritonavir	0	-0.429
raltegravir	0	0.001

(f) Hypertension

	(1) Is Baseline Treatment	(2) Δ QALYs from Baseline
amlodipine	1	0.000
atenolol	0	-0.090
candesartan	0	0.281
candesartan/hydrochlorothiazi	0	0.258
hydrochlorothiazide/irbesartan	0	0.261
hydrochlorothiazide/losartan	0	0.253
irbesartan	0	0.276
losartan	0	0.234
valsartan	0	0.258

Notes: These tables present the estimated QALYs using the CEAR data and applying the regression methodology discussed in the text. Column 1 is an indicator for the index treatment for each condition, which all other QALYs are compared to. The second column is the QALY estimate relative to the index drug.

Figure OA3: QALY Estimates for Individual Treatments for Conditions Not Shown in the Main Text

(a) Lung Cancer

	(1) Is Baseline Treatment	(2) Δ QALYs from Baseline
afatinib	0	0.349
alectinib	0	1.085
bevacizumab/paclitaxel	0	0.371
bevacizumab/pemetrexed	0	0.457
ceritinib	0	0.311
crizotinib	0	0.223
docetaxel	0	-0.101
erlotinib	0	-0.026
gemcitabine	0	0.169
gemcitabine/pemetrexed	0	0.250
nivolumab	0	1.148
osimertinib	0	0.909
paclitaxel	1	0.000
pembrolizumab	0	1.004
pembrolizumab/pemetrexed	0	2.635
pemetrexed	0	0.151
vinorelbine	0	0.035

(b) Multiple Sclerosis

	(1) Is Baseline Treatment	(2) Δ QALYs from Baseline
dimethyl_fumarate	0	0.316
fingolimod	0	0.707
glatiramer	0	-0.259
interferon_beta1a	1	0.000
interferon_beta1b	0	-0.214
natalizumab	0	1.185
ocrelizumab	0	0.657
peginterferon_beta1a	0	0.286
teriflunomide	0	0.311

(c) Osteoporosis

	(1) Is Baseline Treatment	(2) Δ QALYs from Baseline
abaloparatide/alendronate	0	0.075
alendronate	1	0.000
alendronate/teriparatide	0	0.059
denosumab	0	0.074
ibandronate	0	-0.055
risedronate	0	0.010
teriparatide	0	0.057
zoledronic_acid	0	-0.011

(d) Schizophrenia

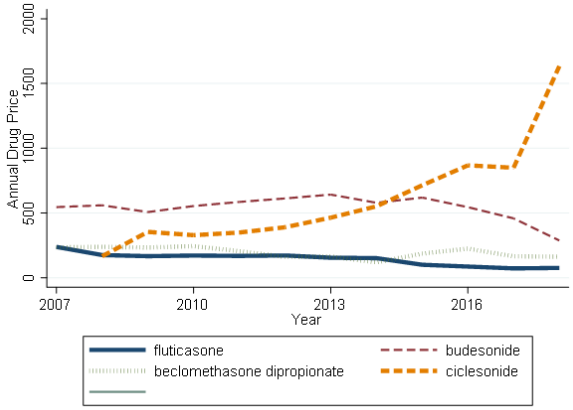
	(1) Is Baseline Treatment	(2) Δ QALYs from Baseline
aripiprazole	0	0.356
clozapine	0	-0.672
haloperidol	0	-0.189
lurasidone	0	0.365
olanzapine	0	0.422
paliperidone	0	0.837
quetiapine	0	-1.068
risperidone	1	0.000
ziprasidone	0	-0.118

(e) Venous Thromboembolism

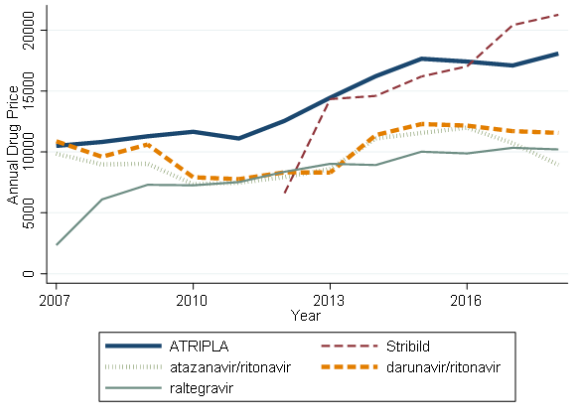
	(1) Is Baseline Treatment	(2) Δ QALYs from Baseline
apixaban	0	0.237
dabigatran	0	0.185
dalteparin	0	0.293
edoxaban/enoxaparin	0	0.318
enoxaparin	0	0.192
enoxaparin/warfarin	0	0.169
rivaroxaban	0	0.200
unfractionated_heparin	0	0.280
warfarin	1	0.000

Notes: These tables present the estimated QALYs using the CEAR data and applying the regression methodology discussed in the text. Column 1 is an indicator for the index treatment for each condition, which all other QALYs are compared to. The second column is the QALY estimate relative to the index drug.

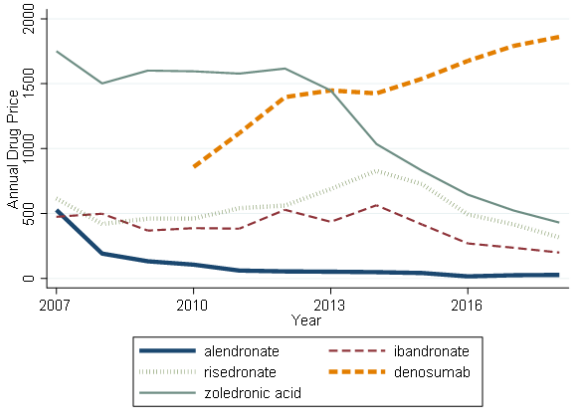
Figure OA4: Prices for the top 5 treatments for selected conditions



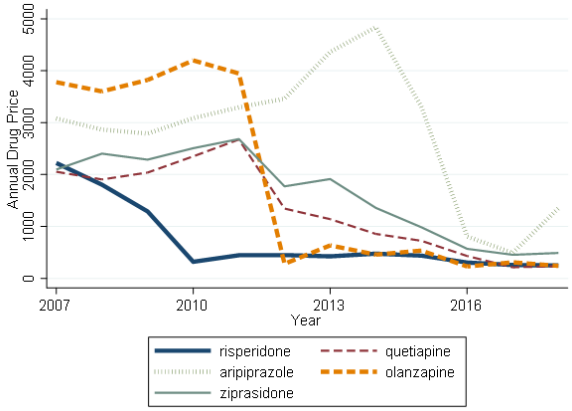
(a) Asthma



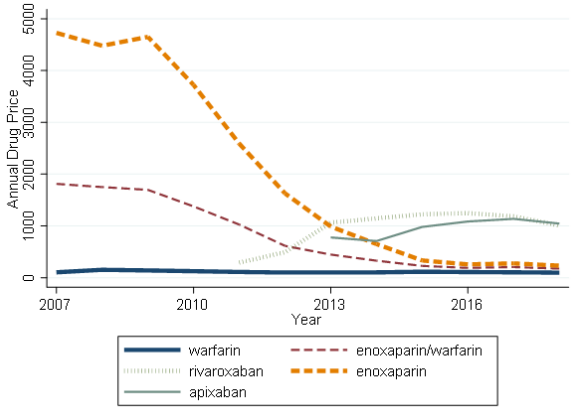
(b) HIV



(c) Osteoporosis



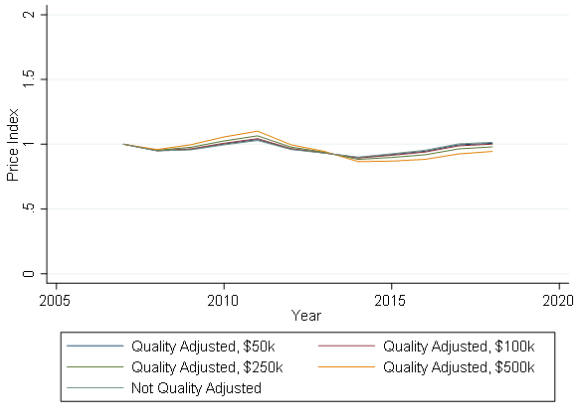
(d) Schizophrenia



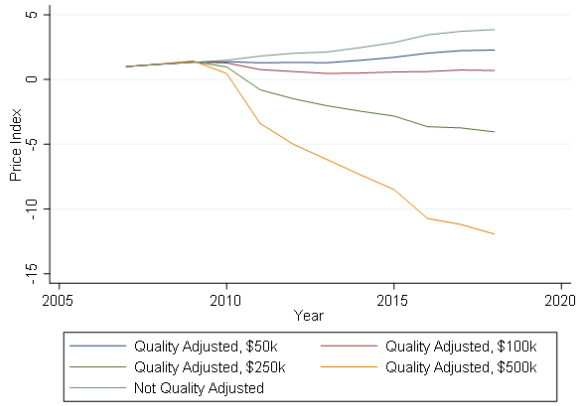
(e) Venous Thromboembolism

Notes: These figures present the average price per year of the 5 highest volume drugs in our sample for conditions not shown in the main text. Drugs do not have prices in all years because either they have not entered the market yet or they stop being used. Prices are from the MarketScan data and are average costs of that drug for a patient who takes that drug in a calendar year. They are *not* scaled to lifetime costs. The drug prices are deflated to 2018 dollars using the PCE deflator and adjusted for rebates using SSR health data.

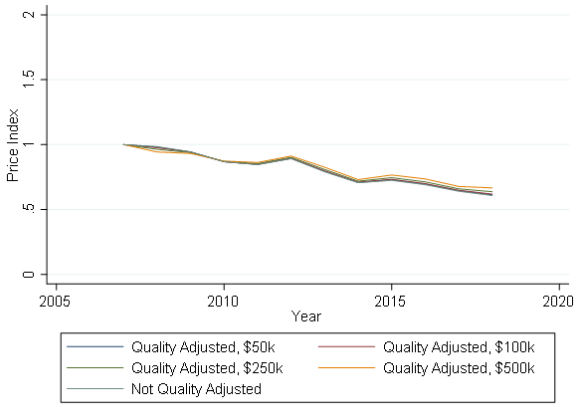
Figure OA5: Price Indexes for Conditions Not Shown in the Main Text



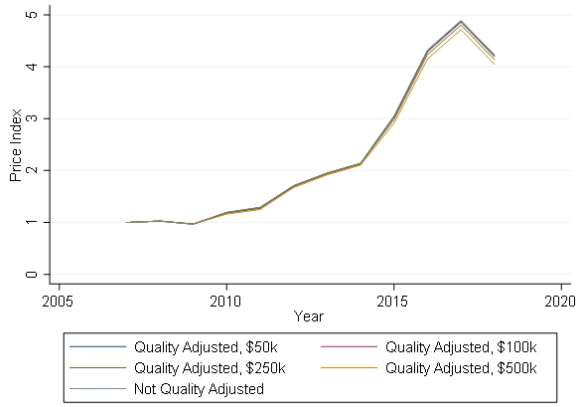
(a) Asthma



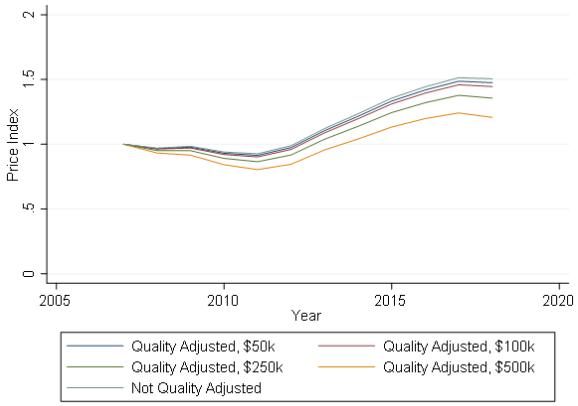
(b) Atrial Fibrillation



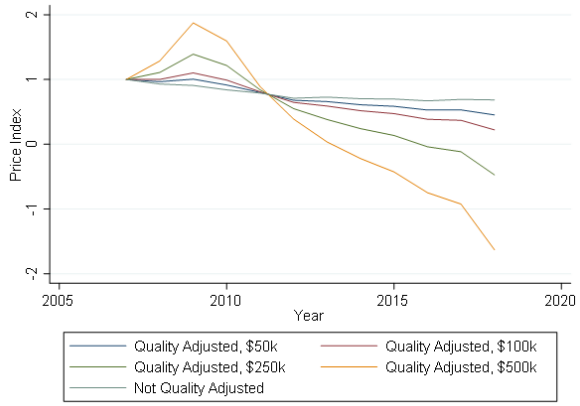
(c) Colon Cancer



(d) Cystic Fibrosis



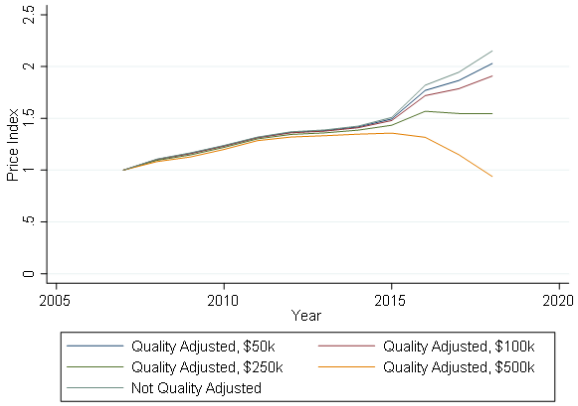
(e) HIV



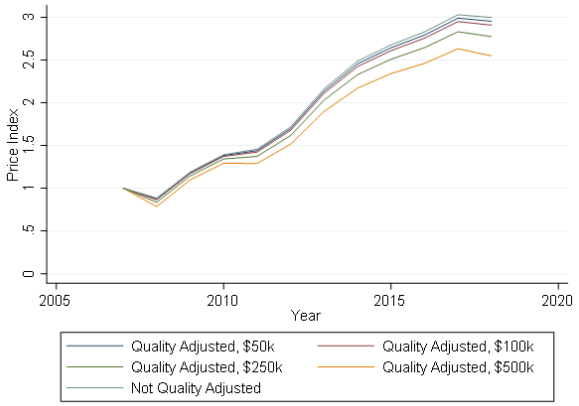
(f) Hypertension

Notes: These figures present quality adjusted price indexes using various assumptions about the value of a statistical life year. These results are constructed using data from CEAR, MarketScan, and SSR Health.

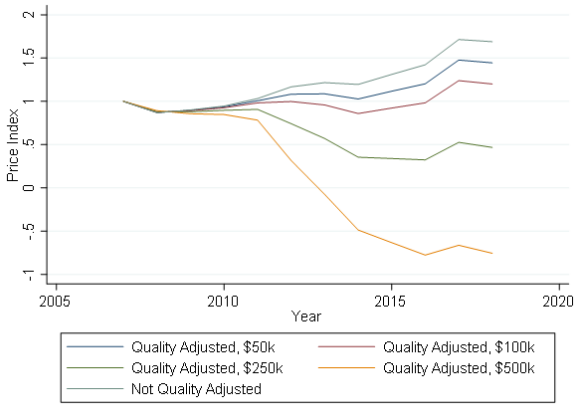
Figure OA6: Price Indexes for Conditions Not Shown in the Main Text



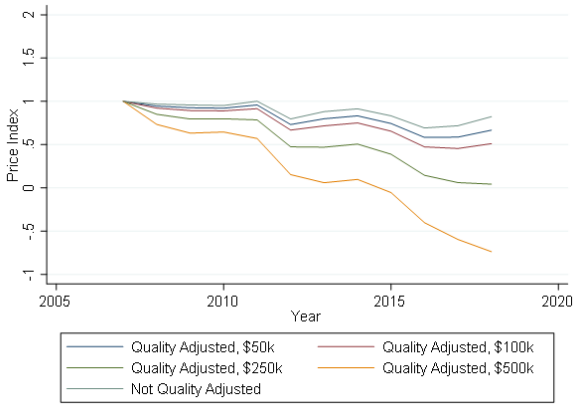
(a) Lung Cancer



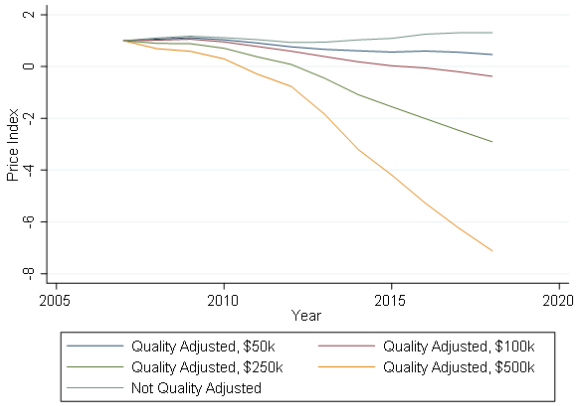
(b) Multiple Sclerosis



(c) Osteoporosis



(d) Schizophrenia



(e) Venous Thromboembolism

Notes: These figures present quality adjusted price indexes using various assumptions about the value of a statistical life year. These results are constructed using data from CEAR, MarketScan, and SSR Health.

Online Appendix OA.B Robustness Checks

OA.B.1 Robustness Checks Referenced in the Main Text

Table OA1: Price Indexes and Changes in Welfare for Each Condition Multiplying QALYs by Two

	(1) Δ Avg QALYs 2018 - 2007	(2) MktScan Lifetime Costs in 2007 ($1,000s)	(3) Price Index $0 VSLY	(4) Price Index $100k VSLY	(5) Δ Consumer Welfare $100k VSLY ($1,000s)	(6) Price Index $500k VSLY	(7) Δ Total Welfare $100k VSLY ($1,000s)
Asthma	0.005	16	1.014	0.986	0	0.875	0
Atrial Fibrillation	0.908	14	3.854	-2.464	50	-27.737	91
Colon Cancer	-0.080	338	0.607	0.631	125	0.726	-8
Cystic Fibrosis	0.463	622	4.232	4.157	-1,963	3.860	46
HIV	0.372	312	1.505	1.386	-121	0.909	37
Hepatitis C	5.766	41	1.204	-12.920	568	-69.416	577
Hypertension	0.079	9	0.684	-0.242	11	-3.946	8
Lung Cancer	1.296	267	2.151	1.666	-178	-0.274	130
Multiple Sclerosis	0.855	476	2.998	2.819	-865	2.099	86
Osteoporosis	0.067	7	1.690	0.711	2	-3.201	7
Rheumatoid Arthritis	0.449	154	2.174	1.883	-136	0.721	45
Schizophrenia	0.235	38	0.823	0.199	30	-2.300	24
Venous Thromboembolism	0.213	6	1.308	-2.063	19	-15.544	21

Notes: This table presents changes in QALYs, costs, quality adjusted price indexes, and consumer and total welfare, constructed using the CEAR, MarketScan, and SSR health datasets. Column 1 presents the difference in average QALYs relative to 2007. Column 2 presents estimated lifetime costs in 2007 for each condition. Column 3 presents unadjusted price index, which is the percentage difference in costs between that year's cost and 2007's cost. Columns 3, 4, and 6 present price indexes assuming the value of a statistical life year (VSLY) is $0, $100k, and $500k, respectively. Columns 5 and 7 present changes in consumer and total welfare. All the estimates in columns 3-7 can be calculated directly using the results in columns 1-3 and using equations 2, 3 and 6 and assuming marginal costs are constant over time.

Table OA2: Price Indexes and Changes in Welfare for Each Condition Multiplying QALYs by One-Half

	(1) Δ Avg QALYs 2018 - 2007	(2) MktScan Lifetime Costs in 2007 ($1,000s)	(3) Price Index $0 VSLY	(4) Price Index $100k VSLY	(5) Δ Consumer Welfare $100k VSLY ($1,000s)	(6) Price Index $500k VSLY	(7) Δ Total Welfare $100k VSLY ($1,000s)
Asthma	0.001	16	1.014	1.007	0	0.979	0
Atrial Fibrillation	0.227	14	3.854	2.275	-18	-4.043	23
Colon Cancer	-0.020	338	0.607	0.613	131	0.637	-2
Cystic Fibrosis	0.116	622	4.232	4.213	-1,998	4.139	12
HIV	0.093	312	1.505	1.475	-149	1.356	9
Hepatitis C	1.442	41	1.204	-2.327	136	-16.451	144
Hypertension	0.020	9	0.684	0.453	5	-0.473	2
Lung Cancer	0.324	267	2.151	2.030	-275	1.545	32
Multiple Sclerosis	0.214	476	2.998	2.954	-929	2.774	21
Osteoporosis	0.017	7	1.690	1.445	-3	0.467	2
Rheumatoid Arthritis	0.112	154	2.174	2.101	-170	1.811	11
Schizophrenia	0.059	38	0.823	0.667	13	0.042	6
Venous Thromboembolism	0.053	6	1.308	0.465	3	-2.905	5

Notes: This table presents changes in QALYs, costs, quality adjusted price indexes, and consumer and total welfare, constructed using the CEAR, MarketScan, and SSR health datasets. Column 1 presents the difference in average QALYs relative to 2007. Column 2 presents estimated lifetime costs in 2007 for each condition. Column 3 presents unadjusted price index, which is the percentage difference in costs between that year's cost and 2007's cost. Columns 3, 4, and 6 present price indexes assuming the value of a statistical life year (VSLY) is $0, $100k, and $500k, respectively. Columns 5 and 7 present changes in consumer and total welfare. All the estimates in columns 3-7 can be calculated directly using the results in columns 1-3 and using equations 2, 3 and 6 and assuming marginal costs are constant over time.

Adding weight to high quality studies, reducing weight to industry affiliated studies:

The CEAR data has a 1-7 measure of study quality, as judged by their readers, where the quality measure depends on whether methods and results were communicated clearly, assumptions were reasonable, and whether sensitivity and subgroup analyses were included. In addition, the CEAR contains a variable that indicates if authors have academic or industry affiliations, and whether the study was sponsored by industry. In Table OA3, we set the weight of each study to its quality score. A study rated as a "7" is weighted seven times as much as study rated as a "1." We also add two points for studies with an author with an academic affiliation and subtract two points if the study had an author with industry affiliation or was sponsored by industry. Results are very similar to the equal weighting results, and are not sensitive to changes in the weighting scheme we use or varying which variables we include.

Table OA3: Price Indexes and Changes in Welfare for Each Condition Increasing Weighting for High Quality Studies

	(1) Δ Avg QALYs 2018 - 2007	(2) MktScan Lifetime Costs in 2007 ($1,000s)	(3) Price Index $0 VSLY	(4) Price Index $100k VSLY	(5) Δ Consumer Welfare $100k VSLY ($1,000s)	(6) Price Index $500k VSLY	(7) Δ Total Welfare $100k VSLY ($1,000s)
Asthma	0.002	16	1.014	0.999	0	0.939	0
Atrial Fibrillation	0.487	14	3.854	0.462	8	-13.109	49
Colon Cancer	-0.037	338	0.607	0.618	129	0.661	-4
Cystic Fibrosis	0.232	622	4.232	4.194	-1,986	4.045	23
HIV	0.192	312	1.505	1.444	-139	1.198	19
Hepatitis C	2.873	41	1.204	-5.833	279	-33.983	287
Hypertension	0.039	9	0.684	0.221	7	-1.633	4
Lung Cancer	0.612	267	2.151	1.922	-246	1.005	61
Multiple Sclerosis	0.414	476	2.998	2.911	-909	2.563	41
Osteoporosis	0.036	7	1.690	1.164	-1	-0.939	4
Rheumatoid Arthritis	0.189	154	2.174	2.051	-162	1.561	19
Schizophrenia	0.125	38	0.823	0.491	19	-0.838	13
Venous Thromboembolism	0.111	6	1.308	-0.457	9	-7.517	11

Notes: This table presents changes in QALYs, costs, quality adjusted price indexes, and consumer and total welfare, constructed using the CEAR, MarketScan, and SSR health datasets. Column 1 presents the difference in average QALYs relative to 2007. Column 2 presents estimated lifetime costs in 2007 for each condition. Column 3 presents unadjusted price index, which is the percentage difference in costs between that year's cost and 2007's cost. Columns 3, 4, and 6 present price indexes assuming the value of a statistical life year (VSLY) is $0, $100k, and $500k, respectively. Columns 5 and 7 present changes in consumer and total welfare. All the estimates in columns 3-7 can be calculated directly using the results in columns 1-3 and using equations 2, 3 and 6 and assuming marginal costs are constant over time.

Table OA4: Price Indexes and Changes in Welfare for Each Condition Using CEAR to Estimate Costs

	(1) Δ Avg QALYs 2018 - 2007	(2) Tufts Costs in 2007 ($1,000s)	(3) Price Index $0 VSLY	(4) Price Index $100k VSLY	(5) Δ Consumer Welfare $100k VSLY ($1,000s)	(6) Price Index $500k VSLY	(7) Δ Total Welfare $100k VSLY ($1,000s)
Asthma	0.002	84	0.995	0.992	1	0.981	0
Atrial Fibrillation	0.454	87	1.292	0.769	20	-1.323	45
Colon Cancer	-0.040	380	0.821	0.832	64	0.874	-4
Cystic Fibrosis	0.231	1,468	2.269	2.254	-1,840	2.190	23
HIV	0.186	1,251	0.977	0.962	48	0.902	19
Hepatitis C	2.883	149	1.239	-0.699	253	-8.450	288
Hypertension	0.039	101	1.044	1.005	0	0.848	4
Lung Cancer	0.648	376	1.169	0.996	1	0.307	65
Multiple Sclerosis	0.428	1,739	1.026	1.001	-3	0.903	43
Osteoporosis	0.033	59	0.995	0.939	4	0.715	3
Rheumatoid Arthritis	0.224	600	1.033	0.996	2	0.846	22
Schizophrenia	0.118	953	0.999	0.986	13	0.937	12
Venous Thromboembolism	0.106	32	0.975	0.644	11	-0.682	11

Notes: This table presents changes in QALYs, costs, quality adjusted price indexes, and consumer and total welfare, constructed using the CEAR, MarketScan, and SSR health datasets. Column 1 presents the difference in average QALYs relative to 2007. Column 2 presents estimated lifetime costs in 2007 for each condition. Column 3 presents unadjusted price index, which is the percentage difference in costs between that year's cost and 2007's cost. Columns 3, 4, and 6 present price indexes assuming the value of a statistical life year (VSLY) is $0, $100k, and $500k, respectively. Columns 5 and 7 present changes in consumer and total welfare. All the estimates in columns 3-7 can be calculated directly using the results in columns 1-3 and using equations 2, 3 and 6 and assuming marginal costs are constant over time.

Table OA5: Counterfactual: Removing All New Drugs - Assuming $50k VSLY

	(1) Baseline Cost Growth 2018 - 2007 ($1,000s)	(2) Cost Growth due to Innovation ($1,000s)	(3) Share of Cost Growth due to Innovation	(4) Δ Consumer Welfare due to Innovation $50k VSLY ($1,000s)	(5) Δ Producer Surplus due to Innovation ($1,000s)	(6) Δ Total Welfare due to Innovation $50k VSLY ($1,000s)
Asthma	0	0	0.292	0	0	0
Atrial Fibrillation	41	8	0.196	31	8	39
Colon Cancer	-133	6	-0.048	-6	6	1
Cystic Fibrosis	2,009	560	0.279	-550	560	9
HIV	158	80	0.505	-76	80	4
Hepatitis C	8	8	1.000	136	8	144
Hypertension	-3	0	0.000	0	0	0
Lung Cancer	308	278	0.904	-246	278	32
Multiple Sclerosis	950	192	0.202	-183	192	9
Osteoporosis	5	2	0.505	-1	2	1
Rheumatoid Arthritis	181	10	0.057	-7	10	3
Schizophrenia	-7	3	-0.415	-1	3	2
Venous Thromboembolism	2	2	1.049	1	2	3
Aggregate	18	4	0.229	-2	4	2

Notes: Column 1 presents the cost growth we see without the counterfactual. This can be calculated as Column 2 multiplied by [Column (3) minus 1] in Table 4. Column 2 tells us the amount of cost growth due to innovation. This is calculated by determining the counterfactual where we replace all "new" drugs with "old" drugs in proportion to "old" drug market share in 2018. We then calculate the cost growth between 2007 and the 2018 counterfactual. Column 2 presents the difference between the cost growth we observe and this counterfactual. Column 3 then computes the share of cost growth that is due to innovation (column 2 divided by column 1). Column 4 presents the change in consumer welfare due to innovation. Column 5 presents producer surplus which is the same as column 2 as we assume marginal costs are constant. Column 6 presents the change in total welfare due to innovation, which is just $100k multiplied by the change in QALYs due to innovation (not shown). These numbers are similar to Table 4 because most of the quality improvements are due to innovation.

Table OA6: Counterfactual: Removing All New Drugs - Assuming $500k VSLY

	(1) Baseline Cost Growth 2018 - 2007 ($1,000s)	(2) Cost Growth due to Innovation ($1,000s)	(3) Share of Cost Growth due to Innovation	(4) Δ Consumer Welfare due to Innovation $500k VSLY ($1,000s)	(5) Δ Producer Surplus due to Innovation ($1,000s)	(6) Δ Total Welfare due to Innovation $500k VSLY ($1,000s)
Asthma	0	0	0.292	0	0	0
Atrial Fibrillation	41	8	0.196	386	8	394
Colon Cancer	-133	6	-0.048	0	6	7
Cystic Fibrosis	2,009	560	0.279	-467	560	93
HIV	158	80	0.505	-41	80	39
Hepatitis C	8	8	1.000	1,434	8	1,442
Hypertension	-3	0	0.000	0	0	0
Lung Cancer	308	278	0.904	45	278	323
Multiple Sclerosis	950	192	0.202	-101	192	91
Osteoporosis	5	2	0.505	12	2	14
Rheumatoid Arthritis	181	10	0.057	24	10	34
Schizophrenia	-7	3	-0.415	15	3	18
Venous Thromboembolism	2	2	1.049	32	2	34
Aggregate	18	4	0.229	20	4	24

Notes: Column 1 presents the cost growth we see without the counterfactual. This can be calculated as Column 2 multiplied by [Column (3) minus 1] in Table 4. Column 2 tells us the amount of cost growth due to innovation. This is calculated by determining the counterfactual where we replace all "new" drugs with "old" drugs in proportion to "old" drug market share in 2018. We then calculate the cost growth between 2007 and the 2018 counterfactual. Column 2 presents the difference between the cost growth we observe and this counterfactual. Column 3 then computes the share of cost growth that is due to innovation (column 2 divided by column 1). Column 4 presents the change in consumer welfare due to innovation. Column 5 presents producer surplus which is the same as column 2 as we assume marginal costs are constant. Column 6 presents the change in total welfare due to innovation, which is just $100k multiplied by the change in QALYs due to innovation (not shown). These numbers are similar to Table 4 because most of the quality improvements are due to innovation.

Table OA7: Price Indexes and Changes in Welfare for Each Condition Between 2007 and 2018 - Marginal Cost is 20% of the Negotiated Price

	(1) Δ Avg QALYs 2018 - 2007	(2) MktScan Lifetime Costs in 2007 ($1,000s)	(3) Price Index $0 VSLY	(4) Price Index $100k VSLY	(5) Δ Consumer Welfare $100k VSLY ($1,000s)	(6) Price Index $500k VSLY	(7) Δ Total Welfare $100k VSLY ($1,000s)
Asthma	0.002	16	1.014	1.000	0	0.944	0
Atrial Fibrillation	0.454	14	3.854	0.695	4	-11.941	37
Colon Cancer	-0.040	338	0.607	0.619	129	0.666	23
Cystic Fibrosis	0.231	622	4.232	4.195	-1,986	4.046	-379
HIV	0.186	312	1.505	1.446	-139	1.207	-13
Hepatitis C	2.883	41	1.204	-5.858	280	-34.106	287
Hypertension	0.039	9	0.684	0.221	7	-1.631	4
Lung Cancer	0.648	267	2.151	1.909	-243	0.939	3
Multiple Sclerosis	0.428	476	2.998	2.909	-908	2.549	-147
Osteoporosis	0.033	7	1.690	1.200	-1	-0.756	2
Rheumatoid Arthritis	0.224	154	2.174	2.029	-159	1.447	-14
Schizophrenia	0.118	38	0.823	0.511	18	-0.738	13
Venous Thromboembolism	0.106	6	1.308	-0.377	9	-7.118	10

Notes: This table presents changes in QALYs, costs, quality adjusted price indexes, and consumer and total welfare, constructed using the CEAR, MarketScan, and SSR health datasets. Column 1 presents the difference in average QALYs relative to 2007. Column 2 presents estimated lifetime costs in 2007 for each condition. Columns 3, 4, and 6 present price indexes assuming the value of a statistical life year (VSLY) is $0, $100k, and $500k, respectively. Columns 5 and 7 present changes in consumer and total welfare assuming VSLY of $100k. All the estimates in columns 3-7 can be calculated directly using the results in columns 1-3 and using equations 2, 3 and 6.

Table OA8: Counterfactual: Removing All New Drugs - Assuming That Marginal Costs are 20% of Negotiated Prices

	(1) Baseline Cost Growth 2018 - 2007 ($1,000s)	(2) Cost Growth due to Innovation ($1,000s)	(3) Share of Cost Growth due to Innovation	(4) Δ Consumer Welfare due to Innovation $100k VSLY ($1,000s)	(5) Δ Producer Surplus due to Innovation ($1,000s)	(6) Δ Total Welfare due to Innovation $100k VSLY ($1,000s)
Asthma	0	0	0.292	0	0	0
Atrial Fibrillation	41	8	0.196	71	6	77
Colon Cancer	-133	6	-0.048	-5	5	0
Cystic Fibrosis	2,009	560	0.279	-541	448	-93
HIV	158	80	0.505	-72	64	-8
Hepatitis C	8	8	1.000	280	7	287
Hypertension	-3	0	0.000	0	0	0
Lung Cancer	308	278	0.904	-213	222	9
Multiple Sclerosis	950	192	0.202	-174	154	-20
Osteoporosis	5	2	0.505	0	2	2
Rheumatoid Arthritis	181	10	0.057	-4	8	5
Schizophrenia	-7	3	-0.415	1	2	3
Venous Thromboembolism	2	2	1.049	5	2	6
Aggregate	18	4	0.229	1	3	4

Notes: Column 1 presents the cost growth we see without the counterfactual. This can be calculated as Column 2 multiplied by [Column (3) minus 1] in Table 4. Column 2 tells us the amount of cost growth due to innovation. This is calculated by determining the counterfactual where we replace all "new" drugs with "old" drugs in proportion to "old" drug market share in 2018. We then calculate the cost growth between 2007 and the 2018 counterfactual. Column 2 presents the difference between the cost growth we observe and this counterfactual. Column 3 then computes the share of cost growth that is due to innovation (column 2 divided by column 1). Unlike with constant marginal costs, column 2 no longer represents producer surplus in our framework, producer surplus is 0.8 multiplied by column 2, which shown in Column 5. Columns 4 and 6 present the change in consumer welfare and total welfare due to innovation.

Table OA9: Counterfactual: Price Indexes and Changes in Welfare for Each Condition Between 2007 and 2018, but Simulating Prices After Drugs Go Off Patent

	(1) Δ Avg QALYs 2018 - 2007	(2) MktScan Lifetime Costs in 2007 ($1,000s)	(3) Price Index $0 VSLY	(4) Price Index $100k VSLY	(5) Δ Consumer Welfare $100k VSLY ($1,000s)	(6) Price Index $500k VSLY	(7) Δ Total Welfare $100k VSLY ($1,000s)
Asthma	0.002	16	1.001	0.987	0	0.931	0
Atrial Fibrillation	0.454	14	3.363	0.204	11	-12.433	45
Colon Cancer	-0.040	338	0.581	0.593	138	0.640	-4
Cystic Fibrosis	0.231	622	2.001	1.964	-599	1.815	23
HIV	0.186	312	0.425	0.365	198	0.127	19
Hepatitis C	2.883	41	0.257	-6.805	319	-35.053	288
Hypertension	0.039	9	0.677	0.214	7	-1.638	4
Lung Cancer	0.648	267	0.952	0.710	78	-0.260	65
Multiple Sclerosis	0.428	476	1.013	0.923	37	0.563	43
Osteoporosis	0.033	7	0.699	0.210	5	-1.746	3
Rheumatoid Arthritis	0.224	154	0.901	0.755	38	0.174	22
Schizophrenia	0.118	38	0.764	0.452	21	-0.797	12
Venous Thromboembolism	0.106	6	0.978	-0.707	11	-7.448	11

Notes: This table presents changes in QALYs, costs, quality adjusted price indexes, and consumer and total welfare, constructed using the CEAR, MarketScan, and SSR health datasets. The results are similar to Table 4, except in 2018 we assume that prices declined by 85% for on-patent drugs. This is meant to simulate a "long-run" outcome where these drugs have lost patent protection. Note that we allow non-drug costs to change between 2007 and 2018, so conditions like atrial fibrillation which have increases in non-drug spending still see unadjusted prices rising.

OA.B.2 Additional Robustness Checks

Multiple Drug Classes — For each condition, in the main results we focus on the most prescribed class of treatments. However, for some conditions we observe are multiple classes of drugs. For example, for rheumatoid arthritis, there are disease-modifying antirheumatic drugs (DMARDs) and non-steroidal anti-inflammatory drugs (NSAIDs). Patients could take medicines in both classes (and often do), as they have distinct purposes. This complicates the regression methodology as not all treatments are directly or indirectly compared to each other. To handle this we create QALY estimates for each class, then weight across classes by quantity. Results are shown in Appendix Table OA10. Results are very similar.

Table OA10: Price Indexes and Changes in Welfare Using Multiple Classes of Treatments

	(1) Δ Avg QALYs 2018 - 2007	(2) MktScan Lifetime Costs in 2007 ($1,000s)	(3) Price Index $0 VSLY	(4) Price Index $100k VSLY	(5) Δ Consumer Welfare $100k VSLY ($1,000s)	(6) Price Index $500k VSLY	(7) Δ Total Welfare $100k VSLY ($1,000s)
Asthma	0.001	16	1.014	1.010	0	0.993	0
Atrial Fibrillation	0.387	14	3.854	1.161	-2	-9.613	39
Colon Cancer	0.055	338	0.607	0.590	138	0.525	5
Cystic Fibrosis	0.231	622	4.232	4.195	-1,986	4.046	23
HIV	0.192	312	1.505	1.444	-139	1.198	19
Hepatitis C	2.883	41	1.204	-5.858	280	-34.106	288
Hypertension	0.016	9	0.684	0.495	4	-0.261	2
Lung Cancer	0.632	267	2.151	1.915	-244	0.968	63
Multiple Sclerosis	0.428	476	2.998	2.909	-908	2.549	43
Osteoporosis	0.030	7	1.690	1.251	-2	-0.505	3
Rheumatoid Arthritis	0.118	154	2.174	2.098	-170	1.793	12
Schizophrenia	0.086	38	0.823	0.594	15	-0.320	9
Venous Thromboembolism	0.106	6	1.308	-0.377	9	-7.118	11

Notes: This table presents changes in QALYs, costs, quality adjusted price indexes, and consumer and total welfare, constructed using the CEAR, MarketScan, and SSR health datasets. Column 1 presents the difference in average QALYs relative to 2007. Column 2 presents estimated lifetime costs in 2007 for each condition. Column 3 presents unadjusted price index, which is the percentage difference in costs between that year's cost and 2007's cost. Columns 3, 4, and 6 present price indexes assuming the value of a statistical life year (VSLY) is $0, $100k, and $500k, respectively. Columns 5 and 7 present changes in consumer and total welfare. All the estimates in columns 3-7 can be calculated directly using the results in columns 1-3 and using equations 2, 3 and 6 and assuming marginal costs are constant over time.

Other Prescription Drug Spending — One challenge is that prescription drug claims do not include diagnosis codes. For our main results, we include inpatient and outpatient claims in baseline annual spending, as well as drugs classified in the CEAR. For this robustness check, we include all drug claims where we observe that drug having once been listed as a treatment for that condition in the MEPS (which has diagnosis codes on drugs). Table OA11 presents results. The MEPS includes treatments which may not focus on the condition at hand, so this likely overstates costs for a given condition. For example, a hepatitis C patient with high cholesterol may be marked as taking a statin on a hepatitis C claim. Hence, we prefer the narrower version of treatments. The unadjusted prices are similar in ordering, but there are some differences in the magnitudes of unadjusted price changes, though they do not systematically overstate or understate cost growth. Quality adjustments are generally smaller as the level of spending with this measure is higher, but overall qualitative results are very similar.

Table OA11: Price Indexes and Changes in Welfare for Each Condition Using Additional Drug Claims

	(1) Δ Avg QALYs 2018 - 2007	(2) MktScan Lifetime Costs in 2007 ($1,000s)	(3) Price Index $0 VSLY	(4) Price Index $100k VSLY	(5) Δ Consumer Welfare $100k VSLY ($1,000s)	(6) Price Index $500k VSLY	(7) Δ Total Welfare $100k VSLY ($1,000s)
Asthma	0.002	49	1.176	1.171	-8	1.152	0
Atrial Fibrillation	0.454	48	2.076	1.130	-6	-2.652	45
Colon Cancer	-0.040	374	0.666	0.677	121	0.720	-4
Cystic Fibrosis	0.231	1,270	5.842	5.823	-6,125	5.751	23
HIV	0.186	795	1.565	1.542	-431	1.448	19
Hepatitis C	2.883	74	1.183	-2.724	275	-18.356	288
Hypertension	0.039	44	1.113	1.024	-1	0.669	4
Lung Cancer	0.648	315	2.028	1.823	-259	1.001	65
Multiple Sclerosis	0.428	829	2.792	2.741	-1,443	2.534	43
Osteoporosis	0.033	31	1.584	1.478	-15	1.055	3
Rheumatoid Arthritis	0.224	261	2.226	2.140	-297	1.796	22
Schizophrenia	0.118	80	0.796	0.650	28	0.065	12
Venous Thromboembolism	0.106	24	1.322	0.881	3	-0.882	11

Notes: This table presents changes in QALYs, costs, quality adjusted price indexes, and consumer and total welfare, constructed using the CEAR, MarketScan, and SSR health datasets. Column 1 presents the difference in average QALYs relative to 2007. Column 2 presents estimated lifetime costs in 2007 for each condition. Column 3 presents unadjusted price index, which is the percentage difference in costs between that year's cost and 2007's cost. Columns 3, 4, and 6 present price indexes assuming the value of a statistical life year (VSLY) is $0, $100k, and $500k, respectively. Columns 5 and 7 present changes in consumer and total welfare. All the estimates in columns 3-7 can be calculated directly using the results in columns 1-3 and using equations 2, 3 and 6 and assuming marginal costs are constant over time.

Alternative QALY Regression Estimates — We also estimate QALYs making different assumptions regarding how the QALY regression (Equation 4) is estimated. Tables OA12 and OA13 show results for QALY changes and price indexes assuming $100k VSLY. Column 1 is the baseline result from Table 4. Column 2 does not normalize for heterogeneity in study assumptions, see Appendix Section OA.D.3 for more details of how we normalize for different assumptions that studies make. Column 3 makes the same heterogeneity adjustments as column 1, but does so on the QALYs in the raw data, before running the regression in Equation 4, rather than adjusting the study fixed effects.

In our main specification, we drop studies which say they are a "placebo," "no treatment," "usual care," "standard of care," and "status quo." We do this because it is often unclear what these treatments are, and we worry that these categories will add a lot of noise or biases.[53] However, dropping these categories drops some studies. In our main regression there were 1,923 comparisons. Adding back placebo and no treatment increases that number

[53]For example, there are cases where placebo makes little sense, like rheumatoid arthritis DMARDs compared against a placebo. Likewise, the standard of care can change. Some studies list what the standard of care is (and we classify those treatments), but we can see the standard of care differs across studies.

to 2,179. Adding back standard of care, usual care, and status quo (on top of no treatment) increases that number to 2,210. Columns 4 and 5 present results with these comparisons added back in. Column 6 estimates the QALY regressions in levels.

Overall, results are quite similar across the board. There are some differences in magnitudes (with hepatitis C and lung cancer being notable cases). However, qualitative conclusions like nearly all conditions having increasing quality, the rough ordering of quality changes, and the sign of quality adjusted price indexes are all consistent for all specifications.

Table OA12: Change in QALYs with different CEAR regression specifications

	(1) Baseline Result	(2) Don't Normalize Heterogeneity	(3) Normalize Heterogeneity First	(4) Add No Treatment	(5) Add Standard of Care	(6) Estimate Regression in Levels
Asthma	0.002	0.006	0.000	0.003	0.003	0.000
Atrial Fibrillation	0.454	0.382	0.515	0.518	0.532	0.453
Colon Cancer	-0.040	-0.106	-0.037	-0.045	-0.045	0.021
Cystic Fibrosis	0.231	0.136	0.128	0.252	0.252	0.192
HIV	0.186	0.091	0.106	0.127	0.131	0.152
Hepatitis C	2.883	1.510	1.718	3.116	3.128	2.317
Hypertension	0.039	0.033	0.030	0.044	0.043	0.044
Lung Cancer	0.648	2.798	1.159	0.685	0.702	0.411
Multiple Sclerosis	0.428	0.400	0.408	0.540	0.564	0.308
Osteoporosis	0.033	0.026	0.031	0.036	0.036	0.022
Rheumatoid Arthritis	0.224	0.266	1.543	0.255	0.257	0.177
Schizophrenia	0.118	0.083	0.007	0.132	0.135	0.008
Venous Thromboembolism	0.106	0.083	0.065	0.120	0.123	0.048

Notes: This table presents estimated changes in average QALYs between 2007 and 2018 using different specifications in our regressions. Column 1 is the baseline result from Table 4. Column 2 does not normalize study heterogeneity. Column 3 normalizes study heterogeneity on the raw QALYs, rather than the study fixed effects. Columns 4 and 5 add additional studies which are less specific about the treatments in the regressions. Column 6 estimates the regressions in levels rather than logs.

Table OA13: $100k VSLY Price Index Results With Different CEAR Regression Specifications

	(1) Baseline Result	(2) Don't Normalize Heterogeneity	(3) Normalize Heterogeneity First	(4) Add No Treatment	(5) Add Standard of Care	(6) Estimate Regression in Levels
Asthma	1.000	0.978	1.013	0.995	0.995	1.013
Atrial Fibrillation	0.695	1.193	0.267	0.247	0.152	0.699
Colon Cancer	0.619	0.638	0.618	0.620	0.620	0.601
Cystic Fibrosis	4.195	4.210	4.211	4.191	4.191	4.201
HIV	1.446	1.476	1.471	1.464	1.463	1.457
Hepatitis C	-5.858	-2.496	-3.004	-6.428	-6.459	-4.471
Hypertension	0.221	0.291	0.328	0.166	0.179	0.163
Lung Cancer	1.909	1.104	1.717	1.895	1.888	1.997
Multiple Sclerosis	2.909	2.914	2.913	2.885	2.880	2.934
Osteoporosis	1.200	1.307	1.237	1.155	1.157	1.359
Rheumatoid Arthritis	2.029	2.002	1.175	2.009	2.008	2.059
Schizophrenia	0.511	0.603	0.804	0.473	0.463	0.802
Venous Thromboembolism	-0.377	-0.005	0.270	-0.601	-0.650	0.543

Notes: This table presents estimated quality adjusted price indexes assuming a $100k VSLY using different specifications in our regressions. Column 1 is the baseline result from Table 4. Column 2 does not normalize study heterogeneity. Column 3 normalizes study heterogeneity on the raw QALYs, rather than the study fixed effects. Columns 4 and 5 add additional studies which are less specific about the treatments in the regressions. Column 6 estimates the regressions in levels rather than logs.

Heterogeneity in treatment effectiveness — One potential bias, noted by Lucarelli et al. (2022), is if there is heterogeneity. For example, if there are different subpopulations where certain treatments work better than others (e.g., different side effects, effectiveness, or preferences for type of treatment). In this case, patients may be matched to treatments that are best for them, which will lead to better health outcomes than if the treatment was randomly assigned in the population. Therefore, our methodology, which compares average quality will understate the benefits of additional treatments if there is heterogeneity.[54] Handling unobserved heterogeneity is a ubiquitous challenge in economics, but especially so when distortions in the market preclude use of revealed preference methods which are typically used to handle unobserved heterogeneity. To try to understand how sensitive our results are to heterogeneity, we take a few approaches. First, we add an unobserved idiosyncratic quality shock to each treatment: For person i the quality of treatment r is: $H_{i,r,d} = \bar{H}_{r,d} + \epsilon_{i,r,d}$, where $\bar{H}_{r,d}$ is our estimate of QALYs in the CEAR. We assume that $\epsilon_{i,r,d}$ has a type 1 extreme value distribution because this distribution has closed form solution for the expected maximum. Then, following Small and Rosen (1981), the expected maximum quality drug

[54]Many cost-effectiveness studies do account for heterogeneity by focusing on specific subpopulations (i.e. estimating QALYs for populations with a certain stage of cancer or a specific genotype of Hepatitis C), but because we cannot always observe these subpopulations in either the CEAR or MarketScan data, we ignore this information. Therefore, our quality estimates may actually be capturing some of the benefits new drugs provide to heterogeneous populations.

for person i is:

$$H_{d,t} = log \sum_{r \in \mathcal{R}_{d,t}} exp(\bar{H}_{r,d}). \tag{A1}$$

For this particular calculation, we ignore market shares, and assume patients receive the expected maximum. Table OA14 shows the results from using Equation A1. Most conditions have higher estimated changes in QALYs, as new entrants unambiguously increase this estimate of consumer welfare. Across all conditions, the unweighted average difference in the change in QALYs across all conditions is 0.766 QALY, which is a sizeable difference. Hypertension has no change in QALYs as it does not have new entrants in our sample. Among the six conditions where consumer welfare was declining at \$100k VSLY in our main results that difference is 0.52 QALYs. Still five of these six conditions had declining consumer welfare (osteoporosis has rising consumer welfare with this number). However, at \$500k VSLY, rheumatoid arthritis and HIV have increasing consumer welfare with this measure.

Table OA14: Price Indexes and Changes in Welfare for Each Condition Allowing for Heterogeneity in Quality using Equation A1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Δ Avg QALYs 2018 - 2007	MktScan Lifetime Costs in 2007 ($1,000s)	Price Index $0 VSLY	Price Index $100k VSLY	Δ Consumer Welfare $100k VSLY ($1,000s)	Price Index $500k VSLY	Δ Total Welfare $100k VSLY ($1,000s)
Asthma	0.266	16	1.014	-0.614	26	-7.129	27
Atrial Fibrillation	1.778	14	3.854	-8.518	137	-58.010	178
Colon Cancer	0.157	338	0.607	0.560	148	0.374	16
Cystic Fibrosis	0.469	622	4.232	4.156	-1,962	3.854	47
HIV	0.425	312	1.505	1.369	-115	0.825	42
Hepatitis C	3.877	41	1.204	-8.293	379	-46.283	388
Hypertension	0.000	9	0.684	0.684	3	0.684	0
Lung Cancer	1.183	267	2.151	1.708	-189	-0.063	118
Multiple Sclerosis	0.258	476	2.998	2.944	-925	2.727	26
Osteoporosis	0.304	7	1.690	-2.781	26	-20.665	30
Rheumatoid Arthritis	0.482	154	2.174	1.862	-133	0.613	48
Schizophrenia	0.151	38	0.823	0.422	22	-1.183	15
Venous Thromboembolism	0.608	6	1.308	-8.330	59	-46.881	61

Notes: This table presents changes in QALYs, costs, quality adjusted price indexes, and consumer and total welfare, constructed using the CEAR, MarketScan, and SSR health datasets. Column 1 presents the difference in average QALYs relative to 2007. Column 2 presents estimated lifetime costs in 2007 for each condition. Column 3 presents unadjusted price index, which is the percentage difference in costs between that year's cost and 2007's cost. Columns 3, 4, and 6 present price indexes assuming the value of a statistical life year (VSLY) is \$0, \$100k, and \$500k, respectively. Columns 5 and 7 present changes in consumer and total welfare. All the estimates in columns 3-7 can be calculated directly using the results in columns 1-3 and using equations 2, 3 and 6 and assuming marginal costs are constant over time.

One issue with this approach to capture heterogeneity is that there is no weighting across treatments in equation A1. Specifically, the quality of a drug that has a 90% share would

be as important as a drug that has a quality of a 10% share in this specification. While the above specification captures the expected maximum quality, one might be concerned that this measure does not capture diffusion well.[55] As another back-of-the-envelope way to address concerns of heterogeneity, we apply insights from Ackerberg and Rysman (2005) to derive a simple functional form for how heterogeneity may increase welfare given a logit functional form.[56] In a logit model where goods are of equal quality (so $\bar{H_{r,d}} = H$), then there is a simple formula for calculating the quality increase as a function of the number of goods:

$$\begin{aligned} H_{d,t} &= log(n_{d,t} \cdot exp(H)) \\ &= log(n_{d,t}) + log(exp(H)) \\ &= log(n_{d,t}) + H \end{aligned} \tag{A2}$$

where $n_{d,t}$ is the number of drugs in the market in year t. This suggests that the quality change is a function of the number of goods in the market $log(n_{d,t})$, assuming this precise functional form. However, the value of the idiosyncratic error is unknown, so we assign a value that provides a reasonable (upper bound) scaling relative to our health measure.[57] Specifically, we impose the assumption that going from one product to two increases the QALYs by 25% of the range of QALYs that we observe for the condition, capturing the value of multiple products in the market. We let R_d be the range of QALYs for disease d (i.e. it is the difference in QALYs between the highest and lowest QALY drug for that treatment in our sample, across all years). Let γ_d be a scaling factor such that $0.25 = (log(2) \cdot R_d/\gamma_d)$. That is, by setting γ_d we impose the assumption that adding a second product increases the QALYs by 25% of the range. We would then calculate an adjusted QALY that adds in $log(n_{d,t}) \cdot \gamma_d$. Specifically, the adjusted amount would be: $H^{alt}_{d,t} = H_{d,t} + log(n_{d,t}) \cdot \gamma_d$, where $H_{d,t}$ is that year's average quality as shown in our main tables. This functional form implies that new drugs will add additional QALYs (beyond impacting the average) as there may be some benefit to having more treatments if there is heterogeneity. However, that benefit diminishes as more drugs enter the market.

Table OA15 shows the results from using Equation A2. All conditions, besides colon cancer and hypertension have larger QALYs, as all conditions except those two had new treatments. Atrial fibrillation, hepatitis C, and lung cancer have particularly large increases in QALYs (compared to Table 4) as each of these conditions have considerable entry during this time period. Rheumatoid arthritis has a fairly large increase as well because its range of

[55] If one is willing to assume preferences are revealed by choices, then one could add unobserved quality that is drug specific to match market shares. However, this term might be picking up features like formulary design, physician learning, or other distortions which are not quality, but do effect choices.

[56] In the context of a choice model, Ackerberg and Rysman (2005) argue that the ϵ's in an i.i.d logit framework may overestimate the value of heterogeneity from new products. Our concern for this robustness check is the opposite, and we actually want to add back in this welfare from heterogeneity.

[57] In contrast to Ackerberg and Rysman (2005) attempting to make an adjustment to remove the idiosyncratic error, we are determining how much of the error to add in.

QALYs across conditions is quite large. Again, five conditions have falling consumer welfare assuming $100k VSLY. At $500k VSLY, cystic fibrosis and multiple sclerosis have falling consumer welfare. In summary, even with what we think are fairly large adjustments to account for heterogeneity, we still find that some innovative conditions have declining consumer welfare during our sample period.

Table OA15: Price Indexes and Changes in Welfare for Each Condition Allowing for Heterogeneity in Quality using Equation A2.

	(1) Δ Avg QALYs 2018 - 2007	(2) MktScan Lifetime Costs in 2007 ($1,000s)	(3) Price Index $0 VSLY	(4) Price Index $100k VSLY	(5) Δ Consumer Welfare $100k VSLY ($1,000s)	(6) Price Index $500k VSLY	(7) Δ Total Welfare $100k VSLY ($1,000s)
Asthma	0.012	16	1.014	0.941	1	0.647	1
Atrial Fibrillation	1.602	14	3.854	-7.297	119	-51.905	160
Colon Cancer	0.060	338	0.607	0.589	139	0.519	6
Cystic Fibrosis	0.318	622	4.232	4.181	-1,977	3.976	32
HIV	0.350	312	1.505	1.393	-123	0.945	35
Hepatitis C	5.050	41	1.204	-11.165	497	-60.643	505
Hypertension	0.039	9	0.684	0.221	7	-1.631	4
Lung Cancer	1.134	267	2.151	1.727	-194	0.029	113
Multiple Sclerosis	0.930	476	2.998	2.803	-857	2.020	93
Osteoporosis	0.047	7	1.690	1.002	0	-1.748	5
Rheumatoid Arthritis	0.575	154	2.174	1.802	-124	0.312	58
Schizophrenia	0.198	38	0.823	0.296	27	-1.813	20
Venous Thromboembolism	0.174	6	1.308	-1.448	15	-12.472	17

Notes: This table presents changes in QALYs, costs, quality adjusted price indexes, and consumer and total welfare, constructed using the CEAR, MarketScan, and SSR health datasets. Column 1 presents the difference in average QALYs relative to 2007. Column 2 presents estimated lifetime costs in 2007 for each condition. Column 3 presents unadjusted price index, which is the percentage difference in costs between that year's cost and 2007's cost. Columns 3, 4, and 6 present price indexes assuming the value of a statistical life year (VSLY) is $0, $100k, and $500k, respectively. Columns 5 and 7 present changes in consumer and total welfare. All the estimates in columns 3-7 can be calculated directly using the results in columns 1-3 and using equations 2, 3 and 6 and assuming marginal costs are constant over time.

Online Appendix OA.C Additional Analyses

OA.C.1 What share of spending growth is due to within-molecule price changes?

In this section we explore what share of spending growth is due to within-molecule price changes. For this counterfactual, we replace the average price of a drug in 2018 with that drug's price in 2007, and recompute a new quantity weighted average cost for that condition in 2018. We leave non-drug spending at the 2018 level. We leave drugs that were not present in 2007 at their 2018 price. That is, for this counterfactual everything in the numerator is

the same as in the observed 2018 data, except price growth (or declines) for "old" drugs.

Table OA16 presents results. Column 1 presents the baseline price index (column 3 of Table 4). Column 2 presents the counterfactual index, where the numerator is the 2018 counterfactual without any within-molecule price growth, and the denominator is what we observe in 2007. For rheumatoid arthritis, if we remove all within-molecule inflation, costs would have *fallen* by 20% during our sample period, rather than grown by over 100%. On the other hand, hypertension costs would have grown by 10%, rather than declining by 32% if 2007 prices remained constant. This is because prices declined after drugs came off patent for hypertension.

Table OA16: Counterfactual: Removing Within-Molecule Price Changes

	(1) Baseline Price Index $0 VSLY	(2) Counterfactual Price Index with Constant Prices	(3) Share of Cost Growth due to Changing Prices
Asthma	1.014	1.135	-8.355
Atrial Fibrillation	3.854	3.898	-0.015
Colon Cancer	0.607	0.895	0.733
Cystic Fibrosis	4.232	3.467	0.237
HIV	1.505	1.404	0.201
Hepatitis C	1.204	1.204	0.000
Hypertension	0.684	1.099	-1.313
Lung Cancer	2.151	2.106	0.039
Multiple Sclerosis	2.998	2.341	0.329
Osteoporosis	1.690	1.726	-0.053
Rheumatoid Arthritis	2.174	0.807	1.164
Schizophrenia	0.823	1.151	-1.854
Venous Thromboembolism	1.308	1.708	-1.299
Aggregate	1.745	1.384	0.484

Notes: Column 1 is the baseline unadjusted price index, same as Table 4. Column 2 tells us what the price index would have in our counterfactual with no within-molecule price growth. To compute this counterfactual we replace all "old" drugs 2018 prices with their 2007 prices. We still use the 2018 market share and for "new" drugs we use the 2018 price. Column 3 then computes the share of cost growth that is due to within-molecule price changes. Some prices decline due to patent expiry, for these conditions the share is negative as within-molecule price changes reduce costs.

The third column shows the share of cost growth that is due to within-molecule inflation. Prices for HIV rise by 50% in our data. Our counterfactual suggests HIV would have grown by 40% in the absence of within-molecule price changes. That is, in the absence of within-molecule price changes, non-drug costs and the mix of drugs used leads to the 40% price increase. Within-molecule price growth would make up the difference, hence within-molecule

price changes only account for 20% of HIV cost growth.[58] In total, six conditions have negative shares, meaning that they would have been more expensive in the absence of within-molecule price growth. All of these conditions had drugs come off patent. Some of these conditions, like atrial fibrillation had very fast cost growth due to new entrants and within-molecule price declines because other drugs came off patent.[59]

Even though half of our conditions have within-molecule price declines, some of the costliest conditions in our sample have considerable within-molecule price changes. In the aggregate, 48% of the price growth that we see for these 13 conditions is due to within-molecule price growth. However, this finding is extremely sensitive to the inclusion of rheumatoid arthritis in our sample. We find about 15% of cost growth is due to within-molecule inflation when not including rheumatoid arthritis.

Online Appendix OA.D Data and Methods Appendix

OA.D.1 Cleaning and classifying the CEAR data

We chose the 13 conditions which were associated with the most studies in the CEAR and seemed appropriate for our analysis. To determine if a comparison is related to that condition, we search the disease or health intervention variable (this is the variable we use to classify conditions and has names like "hepatitis C" or "rheumatoid arthritis"), the ICD-10 code descriptors, ICD-10 chapter descriptors, and the study title for strings that match our condition names. Most of the observations are classified by the disease or health intervention variable.[60]

The key variable in our data is the treatment variable. These are typically a sentence or two long. We tasked multiple research assistants to classify each treatment in the CEAR data to a specific molecule. Each treatment was classified by two research assistants to ensure accuracy.[61] We ignore variations within a molecule like dose (5 mg vs. 10 mg), form (injectable vs. oral), frequency of treatment (once a day vs once a week) and treatment length (12 weeks vs. 24 weeks) as these can be tricky to map into claims data and are not consistently reported in the CEAR data. Often pharmaceutical treatments are vague, only listing a drug class (such as DMARDs for rheumatoid arthritis or direct acting antiretrovirals (DAAs) for HIV), these are marked as missing, since they are not specific enough to credibly map to the MarketScan data. Drugs which are given brand names are mapped back to molecule names (such as brand name "Sovaldi" mapped back to molecule "sofosbuvir").

[58] Like multiple sclerosis, many new HIV drugs raise their price after entry (see Figure OA4). As our results are defining new entry based on a snapshot in time, this counts as cost due to innovation and not within-molecule price growth.

[59] Clopidogrel comes off patent in 2012 and its price drops dramatically (see Figure 5).

[60] We intentionally excluded the abstract from the search variables because of its tendency to pick up the effect of treatment on comorbidities rather than the specific condition intended for the treatment (e.g., whether osteoporosis drugs lead to increased risk of acute myocardial infarction).

[61] We also spent some time classifying procedures. However, procedure names in the CEAR are not standardized and often hard to match to CPT codes in claims data in an accurate way.

Table OA17: How We Define Conditions

Condition	CCS codes or ICD-9 codes
Asthma	CCS=128
Atrial Fibrillation	ATRFIB related ICDs; 4270, 42731, 42732, 42761, 42781, I480, I481, I482, I483, I484, I4891, I4892, I491
Colon Cancer	CCS=14
Cystic Fibrosis	CCS=56
Hepatitis C	Hep-C related ICDs; 07041, 07044, 07051, 07054, 07070, 07071, B1710, B1711, B1920, B1921, B182
HIV	CCS=5
Hypertension	CCS=98 and 99
Lung Cancer	CCS=19
Multiple Sclerosis	CCS=80
Osteoporosis	CCS=206
Rheumatoid Arthritis	CCS=202
Schizophrenia	CCS=659
Venous Thromboembolism	CCS=118

Notes: This table presents how we map from CCS codes (or ICD codes) to conditions in the MarketScan data.

We then merged the CEAR data with the MarketScan data by condition and molecule. To merge by condition we mapped the primary ICD-9 and ICD-10 codes from the Marketscan claims to Clinical Classification System (CCS) categories provided by the Agency for Healthcare and Research Quality (AHRQ) and matched these condition names to those in the CEAR. The only exceptions to using CCS categories were for hepatitis C and atrial fibrillation because the CCS categories for these conditions were too broad. Therefore, instead of using the broad CCS category for "hepatitis," we selected ICD-9 and ICD-10 codes specific to hepatitis C. See Table OA17 below for our mapping of CCS codes or ICD-9/ICD-10 codes to conditions.

To match by molecule we used the treatment names in the CEAR and searched the 2008, 2010, and 2012-18 REDBOOKs for all National Drug Codes (NDCs) associated with these names. Searching across multiple Redbooks ensures that we capture NDCs that enter and exit over time. Likewise, we search the HCPCS-NDC crosswalk for all the HCPCS codes associated with a treatment name. Ultimately, this step ensures that we map CEAR treatments to NDC and HCPCS codes.

The CEAR data often compares combinations of molecules with other combinations

of molecules. In these cases, we view the CEAR quality estimates as being valid for the combinations, so we use the same combinations in the MarketScan data. We used the CEAR data to identify molecules which patients might take in combination. Once the sample of molecules and combinations of molecules is classified in the CEAR, we search for each patient's condition-specific combinations in the MarketScan data. We look at all drugs that patient took in a given year and create combinations based on what they are observed to take. For example, if a hepatitis C diagnosed patient is observed to have taken Ribavirin, Simeprevir, and Sofosbuvir in 2018, then we identify the following seven treatment possibilities: Ribavirin, Simeprevir, Sofosbuvir, Ribavirin/Simeprevir, Ribavirin/Sofosbuvir, Simeprevir/Sofosbuvir, and Ribavirin/Simeprevir/Sofosbuvir. Among the possibilities, we assign this patient to the combination with the most drugs that is also in the CEAR data, where in this example it would be Ribavirin/Simeprevir/Sofosbuvir.

OA.D.2 CEAR Coverage of Spending

To check how well the CEAR data covers the most important treatments, we examine the share of spending we observe in various datasets. For colon cancer and lung cancer most treatments are physician administered and therefore the treatments are in medical claims with diagnosis codes. For other conditions, most treatments are in pharmacy claims which do not include diagnosis codes in the MarketScan data. For those conditions, we use the MEPS data.

For colon cancer and lung cancer, we calculate the share of chemotherapy drugs we classify in the Tufts. To do this, we sum all expenditures on any chemotherapy drugs taken by individuals in our colon and lung cancer samples (where chemotherapy drugs are defined by the BETOS category). We also sum up the expenditures on chemotherapy drugs we classify in Tufts for these conditions. We use the years 2007, 2012, and 2017 to capture the coverage across the entire sample period. For lung cancer, at least 92% of all spending on chemotherapy drugs are in the CEAR data. For colon cancer, that number is at least 85%. In both cases, a majority of the missing spending is for drugs which reduce nausea and other chemotherapy side effects. That is, this analysis suggests we are capturing most of the important chemotherapy drugs for these conditions.

For other conditions, we use the MEPS data to explore CEAR coverage.[62] The MEPS data are useful for this exercise because there are diagnosis codes on pharmaceuticals claims, allowing us to determine the share of MEPS spending we observe in the CEAR. However, the MEPS data do not include 5-digit CPT codes, which limits our ability to measure physician administered drugs. The MEPS also masks some NDCs for expensive drugs for confidentiality reasons, so high cost drugs like Sovaldi are not in the MEPS data. This will bias our results towards zero. We also do not include cystic fibrosis in this analysis, as MEPS masks cystic fibrosis in the data after 2009, again due to confidentiality reasons.

Table OA18 provides evidence of how much spending we can classify. The first column shows the percentage of total spending, in the MEPS, that is pharmaceutical spending for a

[62]For this analysis we combine all years of MEPS data from 2007-2017.

condition (unconditional on whether it is in the Tufts data). For example, 70% of hepatitis C spending is associated with pharmaceuticals (and in the drug files), though this misses some high cost hepatitis C drugs like Sovaldi. Non-pharmaceutical spending includes hospital stays, physician visits, screenings, diagnostic imaging and other non-pharmaceutical spending. As this spending is counted in costs, we are assuming there is no quality improvement for it, which would bias our QALY change results towards zero if those services are improving over time. Another example of this is hypertension, which is mostly treated with pharmaceuticals, but we are picking up a lot of doctor's visits where hypertension is the first listed diagnosis. For atrial fibrillation there is considerable spending on ablation procedures. For venous thromboembolism inferior vena cava filters and thrombectomy/embolectomy are important treatments for some patients. For the remainder of conditions we consider, at least 60% of costs are pharmaceuticals.

The second column shows the share of total drug spending in the MEPS data that is captured by the CEAR data. The MEPS data often contain more classes of drugs that treat a condition, for example painkillers or anti-nausea medication, which are symptom aids that treat many conditions. In addition, comorbidities can inflate spending. For example, if a patient has high cholesterol and hepatitis C, we may see statins in their hepatitis C claims. To better understand how much coverage we have for each condition, column 3 limits to just drugs that have at least 5% market share over the sample period, which drops many of these other drugs. In column 3, we see that we capture at least 79% of spending on drugs that have at least 5% market share for all conditions except atrial fibrillation (60 percent).

Table OA18: Share of MEPS Spending we Classify

	(1) % of All Spending On RX for Condition	(2) % of RX Spending We Categorize in Tufts	(3) % of RX Spending in Tufts on 5% Market Share Drugs
Asthma	65	69	80
Atrial Fibrillation	8	47	60
HIV	71	90	100
Hepatitis C	70	91	100
Hypertension	43	42	79
Multiple Sclerosis	68	92	100
Osteoporosis	70	89	93
Rheumatoid Arthritis	65	85	100
Schizophrenia	52	89	100
Venous Thromboembolism	15	81	85

Notes: This table presents results for how much drug spending in the MEPS we classify in the CEAR. We use the MEPS 2007-2017 data for this analysis. Column 1 presents the share of all spending in the MEPS is pharmaceutical spending, regardless of whether it is in the CEAR data. Column 2 is the amount of all pharmaceutical spending we classify in the CEAR. Some drugs are not in the MEPS as rare/expensive drugs have masked NDC codes. Also, drugs administered by physicians are not included. Both of these will bias our results towards zero. Column 3 is the same as column 2, but only keeps drugs that have 5% market share over the sample period. Cystic fibrosis is not included because MEPS masks that condition to protect anonymity. Lung cancer and colon cancer are not included because their treatments are mostly physician administered, so it is easier to check coverage in the MarketScan data and the MEPS data do not contain information about these treatments.

OA.D.3 Accounting for Heterogeneity in Cost and Quality

Studies in the CEAR data often make various assumptions in calculating their costs and QALYs. For example, a study may vary in the discount rate used, the time horizon considered, or country of interest. In our analysis we include comparison fixed effects which difference out these factors (Equation 4). However, because our results are retransformed including the common effect of a comparison, $\gamma_{u,d}$, we standardize the study common effect based on the characteristics of each study. To do this, we regress our estimate of each comparison's $\gamma_{u,d}$ on the characteristics of the study and predict what the study common effect would have been under consistent assumptions. For this regression, the unit of observation is a comparison. Our regression equation is:

$$\begin{aligned}\hat{\gamma_{u,d}} = \beta_0 &+ \beta_1 \mathbb{1}(\text{Study uses lifetime time horizon}_i) + \beta_2 \text{time horizon}_i + \beta_3 \text{time horizon}_i^2 \\ &+ \beta_4 \text{time horizon}_i^3 + \beta_5 \mathbb{1}(\text{Study discounts the future}_i) + \beta_6 \text{Discount rate}_i \\ &+ \gamma_g + \gamma_a + \gamma_r + \gamma_c \times \mathbb{1}(\text{Treatment is placebo}_i) + \epsilon_i\end{aligned} \tag{A3}$$

where $\hat{\gamma_{u,d}}$ is the estimate of the comparison fixed effect from equation 4. $\gamma_g, \gamma_r, \gamma_c$ are gender,

country, and condition fixed effects, respectively. Studies also include indicators for the age groups included (i.e. 0-18, 19-40, etc.). If the study includes multiple age groups we divide this indicator by the number of age groups included to get a share of the age groups.[63]

Table OA19 presents results from this regression using our baseline sample and assumptions. The columns vary by the variables included. Column (1) does not include the discount rate variables, country fixed effects or condition fixed effects. Column (2) adds in country fixed effects, column (3) adds country and conditions fixed effects. Column (4) includes the discount rate and an indicator for whether there is time discounting. Results are consistent across columns and the signs of coefficients are as expected. Studies with older populations generally have lower QALYs, likely because these populations have less time for the intervention to impact their patients. We see that studies with a lifetime time horizon have higher QALYs. For those that do not, longer time horizons are associated with higher QALYs. We use column (4) as our preferred specification.

[63]For example, if a study has the indicators for 0-18 and 19-40, then we assign 0.5 for each of those variables, rather than 1 for each indicator. Results do not change much if we use indicators rather than shares.

Table OA19: QALY heterogeneity regressions

	(1)	(2)	(3)	(4)
Share 0-18 years old	-0.483*	-0.583**	-0.00656	-0.197
	(-2.47)	(-2.84)	(-0.04)	(-1.44)
Share 19-40 years old	-0.115	0.0167	-0.190	-0.0383
	(-0.76)	(0.11)	(-1.75)	(-0.37)
Share 41-64 years old	0.131	0.171*	0.0452	-0.0297
	(1.49)	(1.99)	(0.69)	(-0.51)
Share 65+	-0.537***	-0.680***	-0.418***	-0.406***
	(-6.71)	(-8.48)	(-5.97)	(-6.64)
Male	-0.359*	-0.255	-0.288*	-0.233*
	(-2.40)	(-1.66)	(-2.44)	(-2.25)
Both Genders	-0.308**	-0.140	-0.144	-0.188
	(-2.80)	(-1.20)	(-1.26)	(-1.88)
Not Specified Gender	-0.400***	-0.327**	-0.181	-0.208*
	(-3.52)	(-2.76)	(-1.56)	(-2.06)
Lifetime Time Horizon	2.958***	2.916***	2.122***	1.385***
	(35.88)	(35.20)	(24.45)	(16.02)
Time Horizon	0.211***	0.219***	0.200***	0.107***
	(18.37)	(18.74)	(19.88)	(10.37)
Time Horizon^2	-0.00421***	-0.00459***	-0.00444***	-0.00198***
	(-10.28)	(-11.50)	(-14.27)	(-6.44)
Time Horizon^3	0.0000252***	0.0000284***	0.0000278***	0.0000109***
	(7.14)	(8.40)	(10.97)	(4.50)
Discount Rate				-0.0747*
				(-2.47)
Constant	-1.923***	-1.868***	-3.217***	-2.396***
	(-14.26)	(-12.59)	(-18.00)	(-11.21)
Country Fixed Effects	No	Yes	Yes	Yes
Condition Fixed Effects	No	No	Yes	Yes
Observations	1058	1058	1058	1058

Notes: This table presents results from different regression specifications from Equation A3. Columns vary by the set of variables included. We use Column 4 as our preferred specification in all other tables.

Using these results, we predict study common effects using standardized assumptions. For the country-specific dummy, we standardize values to the United States. We also specify that the time horizon is a "lifetime" and set the discount rate to be 3 percent. As the demographics change across conditions, we set the demographic variables (age group share and gender indicators) to the mean for that condition in the CEAR data.[64] Tables OA12 and OA13 present QALY estimates and quality adjusted price indexes which check robustness to other assumptions. In particular, we do not adjust for heterogeneity, we adjust the raw QALY (rather than the study fixed effects) for heterogeneity, we add in some additional studies with less precise treatment names, and run the regression in levels. Results are

[64]The one exception is we set the share over 65 to be equal to zero to be consistent with the MarketScan data. Results do not change much when we leave the share over 65 as its average value in the CEAR data.

qualitatively similar regardless of specification.

OA.D.4 Lifetime Costs and Annual Scaling Factor

To calculate lifetime costs we re-scale annual estimates using a scaling factor. In this section we describe how the scaling factor is determined and how it relates to lifetime costs.

We take into account four factors when calculating the scaling factor: time discounting, the probability of dying, the age distribution for condition d, and how costs progress for an individual. Consider a person at age a. Each year s into the future they have the probability of dying $l_{a,s}$, and if they are alive they have expected costs $\hat{C^p_{s,d}}$. Formally, we calculate the estimated lifetime cost for this individual as:

$$LC^p_{a,d} = \sum_{s=0}^{100} (1-\rho)^s \cdot l_{a,s} \cdot \hat{C^p_{s,d}} \tag{A4}$$

where ρ is the interest rate. To be consistent with our standardized QALY estimates, we assume ρ is 0.03. $l_{a,s}$ is the probability of someone age a dying in s periods into the future, which is calculated using the life tables. We then weight across individuals with treatments using the disease-specific distribution of ages in the MarketScan data, $p_{a,d}$.

$$LC^p_{d} = \sum_{a=0}^{100} p_{a,d} \sum_{s=0}^{100} (1-\rho)^s \cdot l_{a,s} \cdot \hat{C^p_{s,d}} \tag{A5}$$

$\hat{C^p_{s,d}}$ measures how costs change after an individual with disease d receives treatment. As our goal is to measure lifetime costs, we want to understand how persistent costs are. For example, some conditions might have costs concentrated in one year (e.g., surgery and chemotherapy for cancer typically occurs in one year) while other conditions may have costs that persist indefinitely. To measure this cost progression, we construct a sample of individuals who are enrolled for four consecutive years after their first treatment and one year prior to treatment (to ensure this is a patient's first treatment). We added the superscript p to $\hat{C^p_{s,d}}$ to indicate this is for our panel of individuals.

Figure OA7 shows how costs evolve for hepatitis C, hypertension, multiple sclerosis, and rheumatoid arthritis. For hepatitis C, in the first year of treatment (year 0), the average cost is \$35,000 while in year 3 the average cost is closer to \$5,000. The steep decline in costs after one year of treatment is because the treatments for hepatitis C are typically taken in one course, rather than indefinitely. One can see this in the median and 75th percentile of costs, which go to zero, as we include individuals enrolled but not treated in our panel.[65]

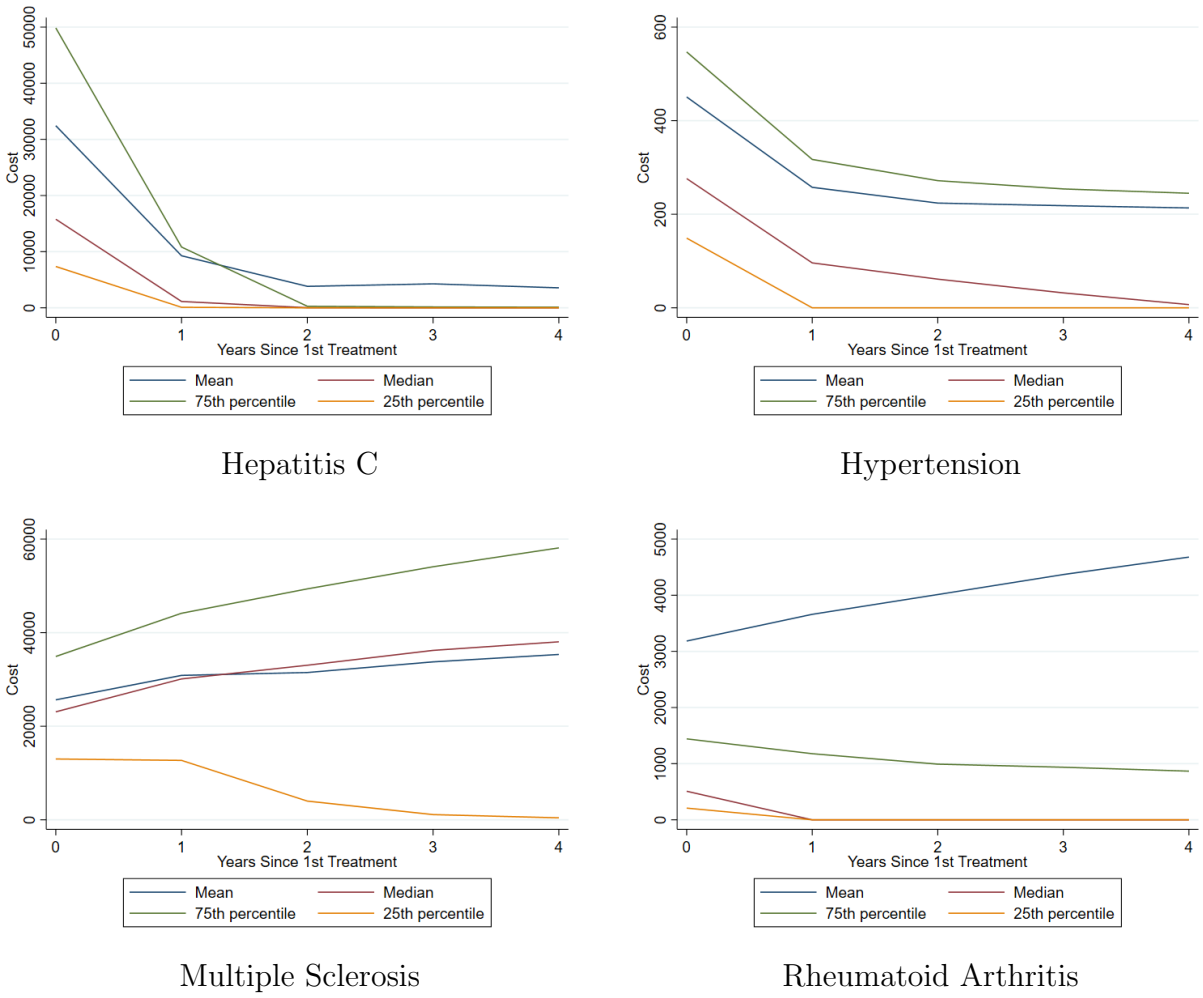
Hypertension has costs which decline from \$600 in year 1 to \$225 in year 3 and 4. Part of this is that in the first year of treatment people may be receiving some additional doctors or

[65] While our annual cost of treatment measure, used in the rest of the paper focuses on individuals with treatment (so we drop those with no treatment in a given year), our panel measure picks up individuals who are enrolled (which is the condition for inclusion in the panel), but may not receive any treatment.

diagnostic visits that are not present in years 3 and 4 once their treatment stabilizes. Therefore, the cost progression captures one expensive year and additional moderately expensive years.

For multiple sclerosis and rheumatoid arthritis, treatments are taken indefinitely, so costs do not necessarily decline over time. The increasing slope for these conditions includes the fact that treatments are getting more expensive over time, which is handled by including year fixed effects in our regressions described below.

Figure OA7: Cost Progression for Selected Conditions



Notes: This figure presents the cost progression for an individual with a treatment for the noted disease. Each year is just the sample mean (or sample percentile) of spending for someone X years from their first treatment year. Everyone gets the treatment in year 0. We follow patients for four additional years and take the average of their spending in each year, including patients with no spending.

To approximate this cost progression and extrapolate out over 100 years, we regress costs

on years since first diagnosis with fixed effects, up to four years, and calendar-year fixed effects using GLM with a log link.[66] We include calendar-year fixed effects because services are getting more expensive over time which inflates the slopes in Figure OA7. After fitting this regression, we predict costs for each year of having the condition using 2007 as the base year.[67] We then plug these estimates into Equations A4 and A5, to get the lifetime cost estimates for our panel of individuals using 2007 as the base, $LC^p_{d,2007}$.

There are two reasons why this lifetime cost estimate differs from the estimates we need. First, costs for individual treatments change over time, whereas this lifetime cost estimate fixes costs in 2007. Second, we need to observe people for a few years to understand how costs evolve, but people who are continuously enrolled for six years or had a year without treatment may have different costs than the average treated person with condition d.

To address the first concern, we multiply $LC^p_{d,2007}$ by $\frac{\bar{C}_{d,t}}{\bar{C}_{d,2007}}$, where $\bar{C}_{d,t}$ is just the average spending on disease d in year t. This captures how annual spending evolves over time for the average treated person. For the second issue, we multiply by $\frac{\bar{C}_{d,2007}}{\hat{C}^p_{1,d,2007}}$, where $\hat{C}^p_{1,d,2007}$ is the predicted average cost, conditional on treatment, for someone in 2007 who fits our six years of continuous enrollment criteria. This adjusts for the sample selection in using people enrolled for multiple years. That is, our cost estimates are:

$$LifetimeCost_{d,t} = LC^p_{d,2007}\frac{\bar{C}_{d,t}}{\bar{C}_{d,2007}}\frac{\bar{C}_{d,2007}}{\hat{C}^p{}_{1,d,2007}} = LC^p_{d,2007}\frac{\bar{C}_{d,t}}{\hat{C}^p{}_{1,d,2007}} \tag{A6}$$

This leads to an intuitive cost multiplier $\frac{LC^p_{d,2007}}{\hat{C}^p{}_{1,d,2007}}$, which is the lifetime cost of the select sample of people enrolled multiple years, divided by the average annual cost of that select sample. Therefore, throughout the draft we compute $\bar{C}_{d,t}$ and multiply it by our cost multiplier:

$$\alpha_d = \frac{LC^p_{d,2007}}{\hat{C}^p{}_{1,d,2007}} \tag{A7}$$

this ratio has an intuitive form, as well, which helps clarify the main assumption we are making. α_d tells us the ratio of lifetime costs to average treatment costs in one year (with treatment) for our continuously enrolled sample. We then assume that this ratio of lifetime costs to one-year costs holds for the main sample.

Table OA20 presents the lifetime cost multiplier we estimate for each condition. Column 4 is the version without accounting for the cost slopes (assuming costs are constant). With constant costs, the life tables and time discounting suggest a lifetime cost multiplier of 23-27.

[66] We use GLM as it has a better fit than log OLS and then applying a retransformation using the smearing estimator in Duan (1983).

[67] In our preferred specification with years since first diagnosis fixed effects, we assume that the year 4 costs remain constant for 96 more years, reflecting a stabilizing in costs. However, we also estimate regressions using a linear trend in years since first treatment. However, this linear trend often goes to zero, which we think understates the persistence of costs. We have also tried higher order polynomials in these regressions, but these results do not seem credible given how far out of sample we are predicting.

The first column is our preferred specification, which assumes that 4th year costs continue indefinitely. For a condition like hepatitis C, our preferred cost multiplier is 3.8. This cost multiplier is much smaller because people mostly only have one expensive year of treatment (i.e. you take one course of Sovaldi). For conditions like rheumatoid arthritis and multiple sclerosis where people continue taking treatments indefinitely, costs are similar to the version without accounting for the cost slope.

Estimated lifetime costs for asthma and hypertension are about half of what they are in the last column, which just takes into account life expectancy. For these conditions, we see some lumpy costs, like doctor's visits and diagnostic tests, which are not paid every year. Likewise, we see that some people stop taking their medications. The annual costs we compute $\bar{C}_{d,t}$ are conditional on having a doctor's visit with an associated diagnosis code and having a treatment, so it likely captures years that are more expensive than the average year. Our lifetime cost estimates, with the panel, accounts for this lumpiness. For these two conditions these cost estimates are telling us an average year is about half as expensive as a year where we observe doctor's visits.

Table OA20: Lifetime estimate cost multipliers for each condition

	(1) Preferred Specification	(2) Uses Years Since Trend Line	(3) No Untreated Prior Year Needed	(4) Constant Costs No Slope
Asthma	12.571	3.733	15.931	27.859
Atrial Fibrillation	8.103	3.064	8.774	24.016
Colon Cancer	7.885	2.241	7.834	23.735
Cystic Fibrosis	23.167	10.109	25.525	28.913
HIV	23.300	14.772	23.965	25.905
Hepatitis C	3.683	1.507	3.659	24.318
Hypertension	12.491	4.561	15.226	24.296
Lung Cancer	7.468	3.128	8.442	23.324
Multiple Sclerosis	22.658	13.653	21.688	25.422
Osteoporosis	7.167	2.845	7.276	23.249
Rheumatoid Arthritis	23.415	16.870	28.219	24.872
Schizophrenia	9.096	2.636	14.704	26.703
Venous Thromboembolism	3.827	1.483	4.435	24.823

Notes: This table presents lifetime estimate cost multipliers for each condition. All columns account for the age distribution of a condition, life expectancy, and the discount rate when calculating lifetime costs. Columns 1-3 account for the idea that when someone has treatment in one year that their future costs may not remain constant. Column 1 keeps costs constant at their year four level. Column 2 uses a log-linear trend to predict costs. Column 3 does not condition on having a year without spending prior to the first year of treatment. Column 4 holds treatment costs constant.

The other columns test the robustness of the assumptions we make. Column (2) uses a linear trend for years since treatment rather than assuming the 4th year remains constant. This ultimately predicts costs trend to zero for most conditions, which we think understates the persistence of costs and is why the results in Column (2) are much lower than Column (1).

Column (3) drops the requirement that we observe one year without diagnosis prior to

the first year. This increases the multiplier estimates because we have more people who are in the constant cost stage of their treatment, reducing the steepness of the slopes in Figure OA7. Results are fairly similar, suggesting that conditioning on having no spending in the prior year does not impact results much.

Tables OA21 and OA22 show the $100k and $250 VSLY estimates using all of these specifications and annual costs (assuming the multiplier is 1). With annual costs prices are falling much more quickly than with constant costs. This is a very wide range of assumed values, results are different and should be viewed as very wide bounds on our central estimates.

Table OA21: Price Indexes for Each Condition Using Different Lifetime Cost Assumptions - $100k VSLY

	(1) Preferred Specification	(2) Uses Years Since Trend Line	(3) No Untreated Prior Year Needed	(4) Constant Costs No Slope	(5) Annual Costs
Asthma	1.000	0.967	1.003	1.008	0.839
Atrial Fibrillation	0.695	-4.499	0.937	2.789	-21.745
Colon Cancer	0.619	0.649	0.619	0.611	0.701
Cystic Fibrosis	4.195	4.146	4.198	4.202	3.369
HIV	1.446	1.411	1.447	1.452	0.116
Hepatitis C	-5.858	-16.059	-5.905	0.134	-24.806
Hypertension	0.221	-0.584	0.305	0.446	-5.100
Lung Cancer	1.909	1.572	1.937	2.074	0.340
Multiple Sclerosis	2.909	2.849	2.905	2.918	0.961
Osteoporosis	1.200	0.458	1.208	1.539	-1.816
Rheumatoid Arthritis	2.029	1.972	2.053	2.037	-1.230
Schizophrenia	0.511	-0.254	0.630	0.717	-2.018
Venous Thromboembolism	-0.377	-3.040	-0.146	1.048	-5.142

Notes: This table presents our quality adjusted price indexes, constructed using the CEAR, MarketScan, and SSR health datasets. Each column assumes that the VSLY is $100k. All columns (except the last) account for the age distribution of a condition, life expectancy, and the discount when calculating lifetime costs. The first three columns account for the idea that when someone has treatment in one year that their future costs may not remain constant. The first column keeps costs constant at their year four level. The second column uses a log-linear trend to predict costs. The third column does not condition on having a year without spending prior to the first year of treatment. The fourth column holds treatment costs constant. Column 5 assumes all costs are in one year, which is clearly unrealistic, but is a clear lower bound.

Table OA22: Price Indexes for Each Condition Using Different Lifetime Cost Assumptions - $500k VSLY

	(1) Preferred Specification	(2) Uses Years Since Trend Line	(3) No Untreated Prior Year Needed	(4) Constant Costs No Slope	(5) Annual Costs
Asthma	0.944	0.779	0.959	0.983	0.135
Atrial Fibrillation	-11.941	-37.915	-10.733	-1.475	-124.142
Colon Cancer	0.666	0.816	0.667	0.627	1.077
Cystic Fibrosis	4.046	3.805	4.063	4.083	-0.080
HIV	1.207	1.035	1.215	1.237	-5.439
Hepatitis C	-34.106	-85.109	-34.341	-4.144	-128.848
Hypertension	-1.631	-5.656	-1.215	-0.506	-28.237
Lung Cancer	0.939	-0.744	1.079	1.763	-6.904
Multiple Sclerosis	2.549	2.252	2.529	2.598	-7.190
Osteoporosis	-0.756	-4.470	-0.719	0.936	-15.836
Rheumatoid Arthritis	1.447	1.165	1.571	1.490	-14.844
Schizophrenia	-0.738	-4.564	-0.143	0.291	-13.380
Venous Thromboembolism	-7.118	-20.432	-5.963	0.009	-30.940

Notes: This table presents our quality adjusted price indexes, constructed using the CEAR, MarketScan, and SSR health datasets. Each column assumes that the VSLY is $500k. All columns (except the last) account for the age distribution of a condition, life expectancy, and the discount when calculating lifetime costs. The first three columns account for the idea that when someone has treatment in one year that their future costs may not remain constant. The first column keeps costs constant at their year four level. The second column uses a log-linear trend to predict costs. The third column does not condition on having a year without spending prior to the first year of treatment. The fourth column holds treatment costs constant. Column 5 assumes all costs are in one year, which is clearly unrealistic, but is also a clear lower bound.

OA.D.5 Rebate Adjustment

To account for manufacturer rebates, we supplement the MarketScan data with data from SSR Health Data. SSR Health, LLC collects data from drug manufacturer SEC filings on revenue net of rebates. They combine the revenue measure with units sold collected by Symphony Health. They then divide net revenues by units sold to estimate a price net of rebate. They also include the wholesale acquisition cost (WAC), an estimate of the manufacturer's list price. At the brand level, we adjust the level of spending in the MarketScan data by multiplying the payment amounts in the MarketScan data by the ratio of the actual revenue divided by the list price, which removes the rebate amount from our cost estimate.

We aggregate the SSR Health data to the brand-year level. Our SSR Health data includes 1,057 different drugs. To apply this in the MarketScan data, we compute one minus the ratio of net prices to list prices (NET/WAC) which we interpret as the share of revenue which is paid in rebates. Then, at the molecule level, we adjust the level of spending in the MarketScan data by multiplying the payment amounts in the MarketScan data by the NET/WAC ratio for each drug we observe in the SSR Health data. If a molecule is missing

in the SSR Health data, which is common (e.g., for most generics), we assume there is no rebate.

Online Appendix OA.E Incorporating Health Risk, Financial Risk, and Insurance Value

In this section, we begin by deriving our consumer welfare measure which follows Cutler et al. (1998) closely, and is also used in cost-effectiveness studies. The measure in Cutler et al. (1998) does not account for insurance or the risk inherent in medical markets. We then build on this measure by incorporating the health risk, financial risk, and the value of health insurance, in the spirit of Lakdawalla et al. (2017).

Suppose an individual derives utility from their health and consumption, $u(C, H)$. The standard approach to deriving consumer welfare gains from innovation is to determine how much a consumer would have to pay to be indifferent between states of the world with and without the innovation, denoted 1 and 0, respectively. This value can be implicitly defined using the following expression:

$$u(Y - S_1 - V, H_1) = u(Y - S_0, H_0)$$

where Y is income, S is the cost of medical care, and H is the health achieved in each state.[68] V is the implicit measure of the consumer welfare generated by the new technology, as it sets utility equal across the two states.

Let u_H and u_C denote the derivatives of the utility function with respect to H and C, respectively. Then taking the full derivative, the value of the new innovation can be derived as:

$$V = \frac{u_H}{u_C}(H_1 - H_0) - (S_1 - S_0) \tag{A8}$$

This is the standard formulation of value of innovation in both the cost-effectiveness literature and the quality-adjusted price index literature. This also matches equation 2, noting that $\frac{u_H}{u_C}$ is the value of health converted into dollars, or the VSLY.

Lakdawalla et al. (2017) note that this "conventional" formulation is missing some important components. First, it does not account for the benefit of reduced risk healthy people face given that they might get sick in the future (health risk): these innovations might improve their welfare if they were to get sick. Second, the conventional formulation does not account for the financial risk that sick people face, namely when someone is sick they also face a cost shock from buying more expensive treatments and potentially lower wages. That is, it does not account for financial risk and the correlation of wage and medical cost shocks.

[68] The cost of the technology is typically including both what an insurer pays and a consumer pays out of pocket, under the assumption that either insurer costs will be passed through to consumers as higher premiums or that we are accounting for the "payer" prospective, which is policy relevant if the payer is a government.

Finally, the conventional measure treats costs paid by the patient and the insurer equally. This ignores the benefit of insurance where risk is spread from sick to healthy individuals. The bias in the conventional approach's measure of the effect of innovation is ambiguous. Higher quality treatments dampen the health shock of being sick. However, if those treatments also have higher costs, then costly new innovations can increase financial risk. This financial risk can be partly mitigated by health insurance.

To incorporate these factors we will consider the ex-ante risk for an individual, prior to knowing whether they will be sick. Let π denote the probability of a individual getting sick. Sick individuals pay P out of pocket for medical care and all individuals pay I for insurance costs. We assume that health status in the healthy state, H_W, does not vary with the innovation. In addition, we let income vary by health status, where Y_W and Y_S denote income for healthy and sick individuals. Then, we can implicitly define the ex-ante value of medical innovation, $V^{ex-ante}$, as:

$$\begin{aligned} \pi u(Y_S - P_1 - I_1 - V^{ex-ante}, H_1) + (1-\pi)u(Y_W - I_1 - V^{ex-ante}, H_W) \\ = \pi u(Y_S - P_0 - I_0, H_0) + (1-\pi)u(Y_W - I_0, H_W) \end{aligned} \tag{A9}$$

Let u_i^S and u_i^W for $i \in \{C, H\}$ denote the derivative of the utility function with respect to i in the sick and well states, respectively. Then taking the total derivative one can derive the amount of ex-ante consumer welfare the new technology provides:

$$V^{ex-ante} = \frac{\pi u_H^S (H_1 - H_0) - \pi u_C^S (P_1 - P_0 + I_1 - I_0) - (1-\pi) u_C^W (I_1 - I_0)}{\pi u_C^S + (1-\pi) u_C^W} \tag{A10}$$

This formulation accounts for the three mechanisms discussed above. The first term makes clear that ex-ante there is a benefit to healthy individuals, as they may get sick with probability π, in which case they will get the health benefits of innovation: $H_1 - H_0$. Second, we differentiate between u_c^S and u_c^W, which allows sick and healthy consumers to have different marginal utilities of consumption, which incorporates financial risk. When patients are sick, they have lower wages, so their marginal utility of consumption can be higher. This happens concurrently with their medical expenses being higher. Finally, sick individuals receive the benefit of insurance, as I shifts costs from sick individuals to healthy individuals.

We follow many of the assumptions in Lakdawalla et al. (2017) to parameterize this new formulation for the value of innovation. In particular, we assume that utility takes the additively separable CRRA form:

$$u(C, H) = \frac{C^{1-\sigma} - 1}{1-\sigma} + \frac{H^{1-\sigma} - 1}{1-\sigma} \tag{A11}$$

This functional form assumption allows us to pin down the marginal utility of consumption terms, u_C^S and u_C^W. To do this, we follow Lakdawalla et al. (2017) and assume that $\sigma = 2$, that income in a well state is \$120,000 and that income in the sick state is 80% of that in the

healthy state. The later assumption is to account for sick individuals' lost wages. We use the observed out-of-pocket costs for each condition to calculate $P_{d,t}$. In our data the out-of-pocket costs are extremely muted by insurance. Conditions like cystic fibrosis, multiple sclerosis, colon cancer, and lung cancer have out-of-pocket costs that are less than 5 percent of the total amount paid. This is because these patients hit their deductibles and out-of-pocket maximums. For cheaper conditions like hypertension, schizophrenia, and asthma, insurance in our data covers between 60-80 percent of the cost. We assume insurance is actuarially fair and higher costs to insurers are fully passed through to all individuals, sick or healthy.[69] Therefore, if we add up the total cost of treatment in the population and divide by the number of individuals with the condition, we obtain the lifetime cost of treatment, $S_{d,t}$, as used in the main specification that ignores insurance. We measure π by calculating the share of individuals in our data with a given disease.[70]

To calibrate u_H^S, we assume the value of a life year for a sick individual, $\frac{u_H^S}{u_C^S}$, is $\$100,000$ in 2007.[71] After that, we allow the level of health in the sick state to vary over time in proportion to the average QALY estimate, but do not impose the VSLY to be equal to $100,000 in other years.[72] We calibrate the VSLY in the sick state to be consistent with the conventional approach (and the main approach in our paper), which focuses on sick individuals and therefore are implicitly assuming a VSLY for a sick individual.

The results in the main draft are consumer welfare for just the sick individuals, and it is assumed there is no welfare gain for individuals that are not sick. We want to construct a comparable measure of welfare using ex-ante consumer welfare, which measures welfare gains for both the sick and healthy populations. To make these measures comparable, we divide our ex-ante consumer welfare by the share of the population that is sick, π, $\frac{V^{ex-ante}}{\pi}$. After dividing by π, the ex-ante consumer welfare measure is comparable to our conventional measure without rescaling V, as both are measures of consumer welfare per sick individual.

Table OA23 presents results for Hepatitis C. Columns 1-3 reproduce the conventional

[69] To calculate insurance costs we sum up all the costs paid by insurers (i.e. total costs minus the out-of-pocket amounts, $S_{d,t} - P_{d,t}$). Then, we divide those costs among the total number of enrollees in our sample, including individuals who do not have condition d. For this exercise, $P_{d,t}$ only includes the 1 year annual cost of treatment (rather than the lifetime cost), because the one year costs are deducted from one year of consumption spending. Note that $S_{d,t}$ remains the lifetime cost of treatment, so future costs are included in the contemporaneous cost of insurance, I_t.

[70] We calculate the prevalence of a condition, π, in 2007. We then keep this value constant, as changing prevalence would muddy the analysis for how innovation shapes welfare. We should also note that prevalence is measured in our under-65 sample. Therefore, the importance of conditions like osteoporosis may be understated relative to a similar analysis with an over-65 population.

[71] Specifically, we calculate the marginal utility of consumption from the sick state u_C^S. We can then calculate the marginal utility of health, u_H^S, by assuming the VSLY is $\$100,000$ and applying the utility function from Equation A11. We back out the level of health in the sick state from this calculation in 2007.

[72] If we held the VSLY fixed at $\$100,000$, then new expensive drugs would increase the marginal utility of health, because they increase the marginal utility of consumption and we are holding the ratio constant. This would mean that the health contribution to utility from drugs with the same QALY estimate would be increasing in their cost, which we do not think is reasonable. Instead, in our approach the VSLY will rise when drugs are cheaper, because individuals are able to consume more, which is consistent with Murphy and Topel (2006).

welfare, health benefit, and cost estimates from Table 2, respectively.[73] Columns 4-6 provide results using $\frac{V^{ex-ante}}{\pi}$. Column 4 presents the full ex-ante value, while column 5 presents just the health benefit (the first term in Equation A10) and column 6 presents the impact the value of the cost change on utility (the second and third term in Equation A10).

In general, the impact on utility from the costs of these technologies are larger using the new framework than the conventional measures (column 3 versus column 6). This is because sick individuals pay higher health care costs with innovation, which causes the marginal utility of consumption to be higher for sick individuals due to the curvature of the utility function. To see this, first consider the full insurance case. In that case, $P_1 = P_0 = 0$ in Equation A10, and I_t is just the total cost of the drugs, spread across the entire population. Because $P_1 = P_0 = 0$, the $I_1 - I_0$ term can be factored out of the second and third terms of Equation A10, so the marginal utility terms and πs cancel out. Ex-ante, an individual will have to pay their share of the cost of the drug in either state, so there is no risk. Hence, the insurance value equals the conventional cost. If insurance is not perfect ($P_t \neq 0$), then the costs are shifted towards the sick state, when the marginal utility of consumption is higher. Sick people also have to pay out-of-pocket costs for their treatments (alongside possible labor market impacts), which means that the utility cost of the price of more expensive treatments is larger than the conventional case with no risk. As discussed above, this is capturing the financial risk created by innovation, so more expensive treatments mean that the financial shock of being sick is larger. However, individuals in our data pay a tiny fraction of the financial cost for these really high cost drugs (for Hepatitis C this is less than 5%), so the effect of financial risk on utility is minimal.[74]

At the same time, the health benefit is larger with the new measure (column 5 versus column 2). This is because it dampens the risk of a health shock, which occurs with a consumption shock. In other words, individuals receive a health benefit when their marginal utility is higher because $\pi u_C^S + (1-\pi)u_C^W < u_C^S$, which means the first term in Equation A10 is larger than the first term in Equation A8.

As discussed above, these different forces are ambiguous. Higher cost treatments may mean that sick people have a larger financial shock when their marginal utility of consumption is higher. However, higher quality treatments dampen the health shock. As shown in Table OA23, for hepatitis, the new formulation always has a larger change in consumer welfare than the conventional approach, so the health effect dominates the cost effect. In 2014, when Sovaldi is dominant in the market, the conventional estimates suggest that consumer welfare is lower than in 2007. Sovaldi's cost is greater than its health benefit in the conventional approach. The new formulation says that consumer welfare is larger in 2014 (relative to 2007). However, the entry of Sovaldi would still reduce consumer welfare relative to 2011-2013, as the health benefit of Sovaldi would not outweigh its cost relative to the Incivek and Victrelis regimen.

[73] In Table 2 in the main text, these are column 5, column 1 times \$100k, and column 2 minus \$41k.

[74] If individuals were uninsured, an \$80k annual course of treatment would represent about 80% of income and the utility impact of these costs would be considerably larger.

Table OA23: Comparing Consumer Welfare With Different Utility Functions: Hepatitis

	(1) Conventional Change in Consumer Welfare	(2) Conventional Change in Health Benefit	(3) Conventional Change in Cost	(4) New Change in Consumer Welfare	(5) New Change in Health Benefit on Utility	(6) New Change in Cost on Utility
2007	0	0	0	0	0	0
2008	2,293	5,370	3,076	5,444	8,524	3,080
2009	5,973	5,436	-537	9,144	8,630	-514
2010	4,522	5,710	1,188	7,832	9,065	1,232
2011	19,491	79,380	59,890	65,266	125,344	60,077
2012	17,823	85,323	67,500	66,838	134,666	67,828
2013	27,522	81,762	54,239	74,536	129,088	54,552
2014	-74,377	225,175	299,552	51,682	351,545	299,863
2015	97,936	272,543	174,607	249,419	424,547	175,128
2016	174,932	273,113	98,180	326,779	425,650	98,871
2017	218,426	288,113	69,687	378,310	448,676	70,366
2018	279,987	288,318	8,331	440,192	449,186	8,994

Notes: This table presents results for Hepatitis C using the conventional measure of welfare and the measure incorporating risk. Columns 1-3 reproduce the conventional welfare, health benefit, and cost estimates from Table 2, respectively. In Table 2 in the main text, these are column 5, column 1 times \$100k, and column 2 minus \$41k. Columns 4-6 provide results using $\frac{V^{ex-ante}}{\pi}$. Column 4 presents the full ex-ante value, while column 5 presents just the health benefit (the first term in Equation A10) and column 6 presents the impact the value of the cost change on utility (the second and third term in Equation A10).

Table OA24 summarizes results for all conditions in 2018. Results are consistent with the table for Hepatitis C. The health benefit tends to be considerably larger. The cost is also larger, but the impact is more muted. On net our measure suggests that benefits of innovation are understated using the conventional measure, and often considerably so. However, even with this new approach, 5 of the 6 conditions where consumer welfare was falling with the conventional approach, are still declining using the new measure.

Table OA24: Summary Comparing Consumer Welfare With Different Utility Functions

	(1) Conventional Change in Consumer Welfare	(2) Conventional Change in Health Benefit	(3) Conventional Change in Cost	(4) New Change in Consumer Welfare	(5) New Change in Health Benefit on Utility	(6) New Change in Cost on Utility
Asthma	-7	229	236	88	354	266
Atrial Fibrillation	4,377	45,388	41,011	29,365	70,625	41,260
Colon Cancer	128,763	-4,025	-132,788	126,370	-6,433	-132,803
Cystic Fibrosis	-1,986,069	23,141	2,009,210	-1,973,320	36,779	2,010,098
HIV	-139,230	18,625	157,855	-128,720	29,556	158,275
Hepatitis C	279,987	288,318	8,331	440,192	449,186	8,994
Hypertension	6,620	3,936	-2,683	8,563	5,839	-2,725
Lung Cancer	-242,725	64,785	307,511	-205,179	102,648	307,827
Multiple Sclerosis	-907,606	42,768	950,374	-885,060	66,298	951,357
Osteoporosis	-1,363	3,326	4,690	470	5,198	4,728
Rheumatoid Arthritis	-158,840	22,444	181,284	-147,095	34,590	181,685
Schizophrenia	18,416	11,755	-6,660	25,171	18,527	-6,644
Venous Thromboembolism	8,685	10,626	1,941	14,550	16,637	2,087

Notes: This table presents results for all conditions in 2018 using the conventional measure of welfare and the measure incorporating risk. Columns 1-3 reproduce the conventional welfare, health benefit, and cost estimates from Table 4, respectively. In Table 4 in the main text, these are column 5, column 1 times \$100k, and column 2 times column 3 minus 1. Columns 4-6 provide results using $\frac{V^{ex-ante}}{\pi}$. Column 4 presents the full ex-ante value, while column 5 presents just the health benefit (the first term in Equation A10) and column 6 presents the impact the value of the cost change on utility (the second and third term in Equation A10).

Online Appendix OA.F Aggregate Measures

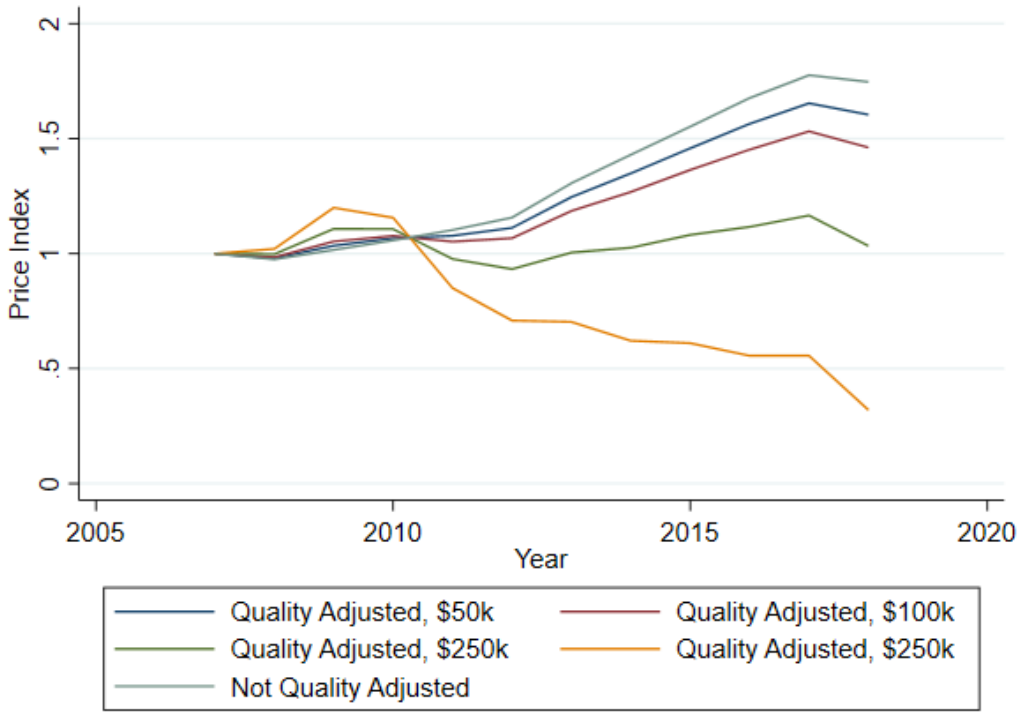
In this section, we aggregate across conditions. However, we caution that we make no claims that these conditions are representative. The amount of heterogeneity across conditions suggests that conditions outside of our sample may have very different trends. Table OA25 and Figure OA8 present results where we aggregate across all the conditions, weighting by their prevalence in 2007. The unadjusted price index for these conditions rose by over 74% in our sample period. However, quality adjustment reduced this to about 46% assuming a \$100k VSLY. At \$500k VSLY, quality-adjusted prices fell by over 68%.

Table OA25: Aggregate Results - Price indexes

	(1) Δ Avg QALYs 2018 - 2007	(2) MktScan Lifetime Costs ($1,000s)	(3) Price Index $0 VSLY	(4) Price Index $100k VSLY	(5) Δ Consumer Welfare $100k VSLY ($1,000s)	(6) Price Index $500k VSLY	(7) Δ Total Welfare $100k VSLY ($1,000s)
2007	0.000	23,812	1.000	1.000	0	1.000	0
2008	-0.002	23,214	0.975	0.984	0	1.020	-0
2009	-0.009	24,196	1.016	1.053	-1	1.199	-1
2010	-0.005	25,176	1.057	1.077	-2	1.156	-0
2011	0.012	26,257	1.103	1.052	-1	0.850	1
2012	0.021	27,540	1.157	1.067	-1	0.709	2
2013	0.029	31,100	1.306	1.185	-5	0.703	3
2014	0.039	34,049	1.430	1.268	-6	0.621	4
2015	0.045	36,962	1.552	1.364	-9	0.610	5
2016	0.053	39,924	1.677	1.452	-11	0.556	5
2017	0.058	42,287	1.776	1.532	-13	0.556	6
2018	0.068	41,599	1.747	1.461	-11	0.319	7

Notes: This table presents changes in QALYs, costs, quality adjusted price indexes, and consumer welfare aggregated across all conditions. In this table, changes in QALYs, costs, and welfare are quantity weighted. Price indexes are revenue weighted. Column 1 presents the difference in average QALYs relative to 2007. Column 2 presents estimated lifetime costs in each year. Columns 3, 4, and 6 present price indexes assuming the value of a statistical life year (VSLY) is $0, $100k, and $500k, respectively. Columns 5 and 7 present changes in consumer welfare. All the estimates in columns 3-7 can be calculated directly using the results in columns 1-3 and using equations 2 and 3. The price indexes are also graphed in Figure OA8.

Figure OA8: Aggregate Price Indexes



Notes: This figure presents quality adjusted price indexes weighted across conditions by spending. The $0 VSLY, $100k VSLY, and $500k VSLY indexes are also shown in Table OA25. These results are constructed using data from CEAR, MarketScan, and SSR Health.

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